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A Macroeconomic Investigation of the Labor Market Matching Efficiency

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A MACROECONOMIC INVESTIGATION OF THE

LABOR MARKET MATCHING EFFICIENCY

By

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An Abstract of the Thesis Presented
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The first section of this research explores how traditional measures of unemployment can mask important changes in the labour market across the business cycle. We therefore use broader definitions of unemployment to estimate time-varying job-matching efficiency rates that are consistent with vacancies and hiring activity data for the U.S. Our efficiency rates are then modelled along with employment data to study their dynamic, non-linear relationship. We find that including part-time workers for economic reasons as well as marginally attached workers helps explain the changes in employment patterns observed after the global financial crisis, emphasizing the importance of accounting for underemployment, particularly in the last decade.

The second section of this research conducts a preliminary analysis of a new coincident and leading composite index following the structural changes inflicted on the economy after the great recession. Since the recession, many critical aspects of the economy have changed; from interest rates near the zero-lower bound, record low levels of unemployment, falling labor force participation, and stagnant inflation and wages. This paper takes a novel approach by including the match efficiency parameter as a leading indicator to incorporate a broader view of the labor

market. We find that including the match efficiency with other more established indicators improves the composite index.

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CHAPTER 1

INTRODUCTION

1.1. Background

Over the last two decades there have been dramatic swings in the unemployment rate and job vacancy rate. Following the great recession, there was high unemployment and an excess supply for labor. Now the hires per vacancy rate is currently below 1, suggesting that there is demand for labor that is difficult to fill (Dreier et al., 2020). This is partially due to the lowest labor force participation rate since the 1980's (Bown and Freund, 2019), which has a knock-on effect of pushing the unemployment rate below 4%. Despite this demand, wage growth has been relatively stagnant during the recovery and underemployment of workers creates added frictions (Bell and Blanchflower, 2018). This evidence leads researchers to question of whether the labor market is truly as healthy as it appears.

One way to analyze this question is through the labor market matching function from the seminal work of Blanchard and Diamond (1989). Since the last recession, economists have looked at mismatch occurring in the labor market. Abraham (2015), among others, find that there is skill and geographical mismatch that has persisted from the recession and is affecting recovery. To address the mismatch, pervious work has looked at the matching function, specifically labor market match efficiency. We find that, in the short run, high match efficiency is connected to a growth in employment while in the long run it is connected to a decrease in employment (Crawley and Welch, 2019). This is likely due to a variety of reasons; one explanation is that the low level of unemployment increases the match efficiency, and when unemployment and vacancies converge it becomes difficult for firms to hire, leading to a decrease in the employment rate (Crawley and Welch, 2019).

Underlying frictions in the labor market lead to questions about underlying frictions in the economy as a whole. Since the last recession, macroeconomic modeling has received much criticism due to high levels of complexity and subjectivity in the models (Romer, 2016). In addition to low levels of labor force participation and high levels of vacancies, interest rates have also behaved differently after the recovery from the recession. For decades the slope of the yield curve, or the spread between long-term and short-term interest rates, has been used as predictor of economic activity (see for example Campbell, 1995; Dueker, 1997). However, due to quantitative easing following the great recession interest rates have been at or near the zero-lower bound, which calls the reliability of the yield curve as an economic indicator into question (Baumeister and Benati, 2010).

Reliable indicators are incredibly important when analyzing economic activity. One method of using indicators is through a composite index, which applies normalization and weighting mechanisms to a variety of variables that lead or coincide with changes in cyclical economic activity. When analyzing the labor market, common indicators are the unemployment rate, employment, or employee payroll hours. However, all three of these regularly move with or after changes in cyclical activity. Due to the observable frictions that are occurring in the labor market despite a strong economy during the expansion, the match efficiency could be a leading indicator for economic activity. It is imperative to note that this research was done prior to the COVID-19 pandemic that changed the global economy in early 2020. Labor markets and economic indicators look drastically different now, but it is critical to analyze the patterns and frictions that were occurring during the expansion in order to understand what could happen in the future.

1.2. Purpose of Research

To gain a better understanding of economic activity and labor market dynamics following the recession, this thesis asks four research questions. The first two questions are:

1. *How do alternative measures of unemployment change the labor market matching efficiency?*
2. *Within a matching function framework, have labor market dynamics changed since the great recession?*

Question one is based off the notion that including workers who are underemployed and marginally attached to the labor market in the unemployment rate may provide a more accurate look at the matching function. By investigating alternative definitions of unemployment in the matching function and how that is connected to employment, the second research question can be analyzed. After investigating the first two questions, it will be important to relate the labor market dynamics back to the real economy, yielding the third and fourth research questions:

3. *Can the match efficiency be used as an effective indicator in a composite economic index?*
4. *Following the great recession, how does a composite index look now?*

1.3. Thesis Organization

The remainder of this document consists of two chapters that seek to analyze labor market matching functions and composite indices in order to answer the research questions. The second chapter attempts to answer questions 1 and 2 by calculating match efficiencies using multiple definitions of unemployment and then running a non-linear dynamic correlation with the employment rate for periods before and after the recession. The third chapter attempts to answer questions 3 and 4 by constructing coincident and leading economic indices which include the match efficiency as an indicator.

CHAPTER 2

MATCHING EFFICIENCIES AND EMPLOYMENT GROWTH: WHICH MATCH IS THE MATCH?

The following chapter is a variation of work with Dr. Andrew Crawley and Dr. Julieta Yung.

2.1. Introduction

The United States has been experiencing an unprecedented level of low unemployment following a decade of growth. While in the short run this might be considered a positive situation, resulting market inefficiencies over a prolonged period of time could be detrimental to the economy. Behind this healthy picture, some are questioning how these decreases in unemployment affect the employment rate. During this expansionary cycle, job vacancies are rising at a faster rate than matches have been made. Although past research has examined the declining labor force participation rate (see for example Krueger, 2017; Bown and Freund, 2019), less attention has been paid to the efficiency of the macro labor matching process over this period of time (Crawley and Welch, 2019). This paper utilizes different measures of unemployment to calculate labor market matching efficiencies using the seminal matching function from Blanchard and Diamond (1989). These efficiencies are then dynamically correlated to the employment rate to discover which matching measure is more reflective of the labor market.

The labor matching process has been a source of economic inquiry for decades following the work of Diamond (1982), Mortensen and Pissarides (1994). How a market clears is connected to the level of unemployment present. Traditional theory would suggest that as the level of unemployment falls, the number of available workers decreases, and the equilibrium wage rate rises, to see workers take up employment (Phelps, 1968). In the present US economy, wage rates have remained static at a time of falling numbers in the labor force, suggesting that the matching process may be less efficient (Crawley and Welch, 2019). Taking a look at historic data, there are indications from the temporal dynamics that as U-3 and vacancies move closer to convergence, the economy enters a recession; once this occurs the data series quickly diverge as unemployment rises.

Figure 2.1 plots the traditional measure of unemployment, U-3 and vacancies overtime from 1967 thru 2018. For the first time since the 1970s, the United States' job vacancy rate has surpassed the traditional measure of unemployment, U-3. This is also coupled with criticism on whether the unemployment rate is an accurate and reliable indicator of labor market health (Bell and Blanchflower, 2018; Feng and Hu, 2018). This is not a new critique and as far back as Bregger and Haugen (1995) questions have been posited about the reliability of different CPS classifications.

Figure 2.1. Unemployment Rate and Vacancy Rate (1967-2018)

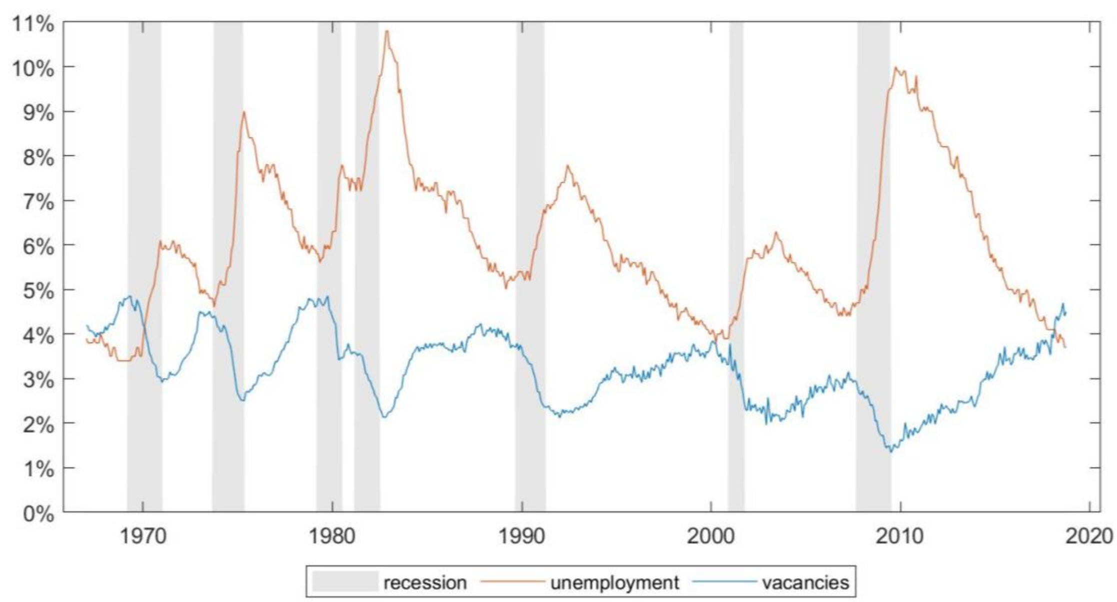


Figure 2.1 supports the notion that, over time, changes in labor market dynamics could influence how the unemployment rate is classified (Bregger and Haugen, 1995; Kingdon and Knight, 2006). Both papers highlight how different labor market conditions change and a reconsideration of unemployment is needed. Kingdon and Knight (2006) focus on the inclusion of 'discouraged workers' and their importance in non-searching unemployed and find they make up a large proportion of those out of work. It has also been suggested that in recent years the unemployment rate understates the level of slack prevailing in most OECD countries, with stagnant wages as evidence of a structural change (Bell and Blanchflower, 2018).

Bell and Blanchflower (2018) address the notion of underemployment in the UK, where workers demand more hours but cannot access them at the going wage rate. Thus, despite low unemployment, workers have a lower bargaining power than they should theoretically. Bell and Blanchflower (2018) also claim that this phenomenon is new since the 2008 recession and could be caused by a variety of reasons, such as broader educational attainment, higher self-employment, and lower worker productivity. While their empirical research is done primarily in the UK and Europe, there is evidence from Figure 2.1 that an underrepresentation of labor market frictions is also occurring in the United States

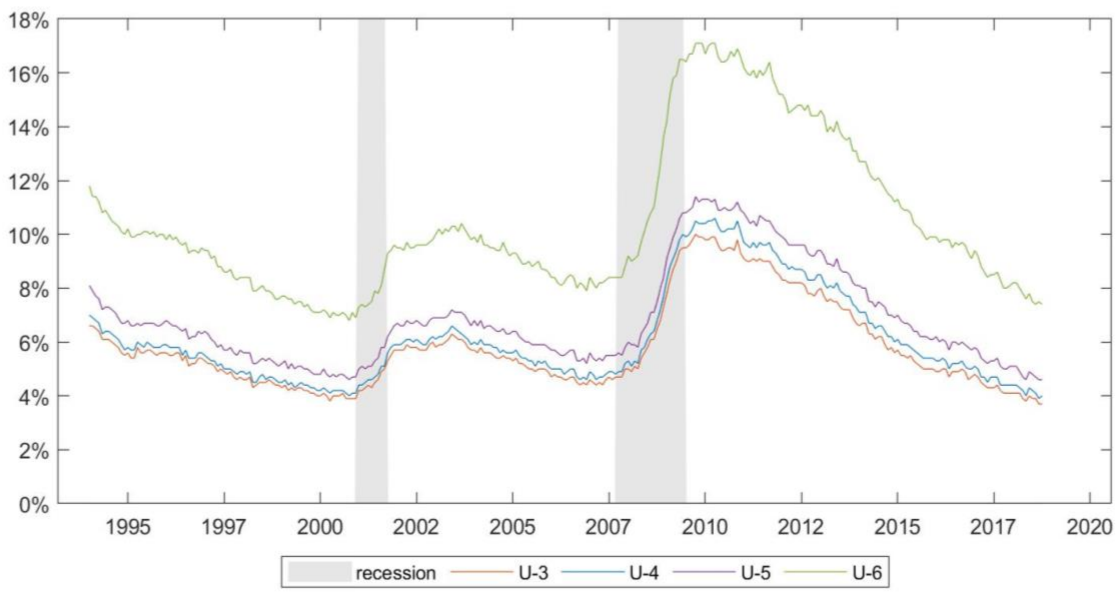
An alternative approach is to look beyond traditional unemployment (U-3) in the matching process by incorporating discouraged workers, marginally attached workers, and those working part time for economic reasons, found in U-4, U-5, and U-6 BLS definitions respectively. Structural issues amplify the possible mismatch present in the labor market and may be observed in some unemployment definitions but not others (Feldman, 1996; Bell and Blanchflower, 2018). This allows a range of estimates on the efficiency of the market. The official definitions from the

Bureau of Labor Statistics are presented in Table 2.1 and the unemployment rates from 1994-2018 is plotted in Figure 2.2.

Table 2.1. Alternative Measures of Unemployment (U-3 thru U-6)

U:	**BLS Definition:**
U3	Total unemployed (official unemployment rate).
U4	Total unemployed plus discouraged workers.
U5	Total unemployed, plus discouraged workers, plus all other persons marginally attached to the labor force
U6	Total unemployed, plus all persons marginally attached to the labor force, plus total employed part time for economic reasons.

Figure 2.2. Alternative Measures of Unemployment (U-3 thru U-6)



Given the complexity of the matching process in the labor market, an important academic pursuit is to understand the frictions in the relationship between unemployment and vacancies and explore its connection to the employment rate. In the literature to date, authors have lamented on the notions of geographical or skill mismatch as well as disequilibrium in wages or hours available (Gobillion et al., 2007; Mavromaras and Sloane, 2015). No work has attempted to establish a direct empirical link between the matching process and the employment rate.

The aim of this paper is to address this gap in the literature. Given the critique by some of the current measure of unemployment, this work goes further by estimating the matching efficiency using different measures of unemployment. All unemployment[1] data used is from the Bureau of Labor Statistics' Current Employment Survey (CES) and Labor Force Statistics from the Current Population Survey (CPS). The vacancies[2] and hires[3] data from 2001-2018 are from Bureau of Labor Statistics Job Openings and Labor Turnover Survey (JOLTS). Employment rate data is from OECD Main Economic Indicators database, retrieved from Federal Reserve Economic Database.

The paper is structured as follows: the first section presents the foundations of the matching efficiency followed by how this is assessed empirically. The paper then goes through the multi-procedural approach used, first estimating labor market congestion, then calculating different matching efficiencies, including assessing their cyclicality. Finally, all these pieces are connected to run a dynamic correlation assess the relationship between matching efficiency and the employment rate.

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1 U-3 unemployment is collected monthly from 1967-2018. U-4, U-5, and U-6 data is collected monthly from 1994-2018.

2 Monthly vacancy data from 1967 -2000 is obtained using the approach of https://www.sciencedirect.com/science/article/pii/S0165176510002934.

3 Monthly hires data from 1994 – 2000 are obtained from a modified synthetic JOLTS estimation from Davis et al. (2012). More details on this modification can be found in Appendix A.

2.2. Foundations of the Matching Function

The matching model of Mortensen and Pissarides (1994) has become the cornerstone of the job search literature. This work provides a way of connecting endogenous job creation and job destruction over the business cycle and exists independent of other processes which affect aggregate conditions. To begin to utilize this framework, we need to construct some basic labor market flow identities[4]. It is assumed that the labor force can be decomposed into its two constituent components this is noted in equation (1):

(1) $L = E + U$

where L represents the labor force, E is the number of employed workers, and U is the number of unemployed workers. The second identity in the model is:

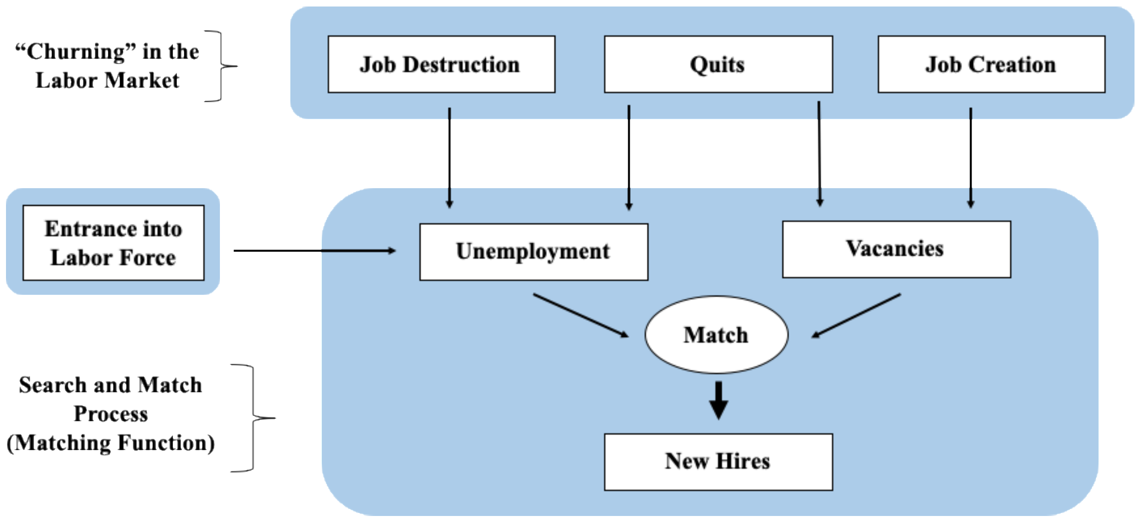
(2) $K = F + V + I$

where K is the total number of jobs, F is the number of filled jobs, V is the number of vacancies, and I is the number of idle jobs, which represents jobs that are unfilled, but no vacancies are posted.

Blanchard and Diamond (1989) examined flows between vacancies and unemployment through a Beveridge curve and matching function framework[5]. Figure 2.3 illustrates the process of job creations and job destruction[6].

4 Lipsey (1960)
5 There is a strong body of literature on empirical and theoretical matching functions from the late 20th century which Petrongolo and Pissarides (2001) go to great depths on.
6 Modified from the work of Bleakley and Fuhrer (1997).

Figure 2.3. A Simple Model of Labor Market Flows and the Matching Process



Job destruction, quits, and workers entering into the labor force make up the flows into unemployment, while jobs created and openings from people who quit their jobs turn into vacancies. The matching function allows for the analysis of the relationship between unemployment and vacancies in a functional form. In its most basic form, the matching function can be written as:

(3) $M = m(U, V)$

In a continuous-time model, M is the instantaneous rate of job matching between the unemployed (U) and jobs vacant (V), with m being an efficiency parameter. In theory when frictions do not exit it is possible to denote matches as being:

(4) $M = \min(U, V)$

This is difficult to measure empirically given the continuous gap between vacancies and unemployment (Petrongolo and Pissarides, 2001). When frictions (m) do exist, they are challenging to model in continuous time with discrete data. One might think of this in the same way as an aggregate production function, where frictions exist even in an extremely efficient condition (Blanchard and Diamond, 1989). It's possible to link this process in a functional form to hiring.

This can be expressed in Cobb-Douglas form as:

(5) $H = mU^{\gamma}V^{1-\gamma}$

where H are hires, γ represents the degree of congestion[7] in the labor market and m remains the parameter denoting the efficiency of the matching process. This style of matching function is used across macroeconomic models (Pissarides, 2000) and is at the heart of this present paper.

The Beveridge curve is a visual tool to analyze labor market dynamics. In theory, movement along the curve represents cyclical changes (Dow and Dicks-Mireaux, 1958; Lilien, 1982). Confirmed by the inverse relationship, unemployment and vacancies move in opposite cyclical frequencies (Elsby et al., 2015). However, a rightward shift in the curve indicates a higher degree of mismatch, or inefficiency, in the labor market (Dow and Dicks-Mireaux, 1958; Diamond, 1982). Figure 2.4 shows the theoretical Beveridge curve.

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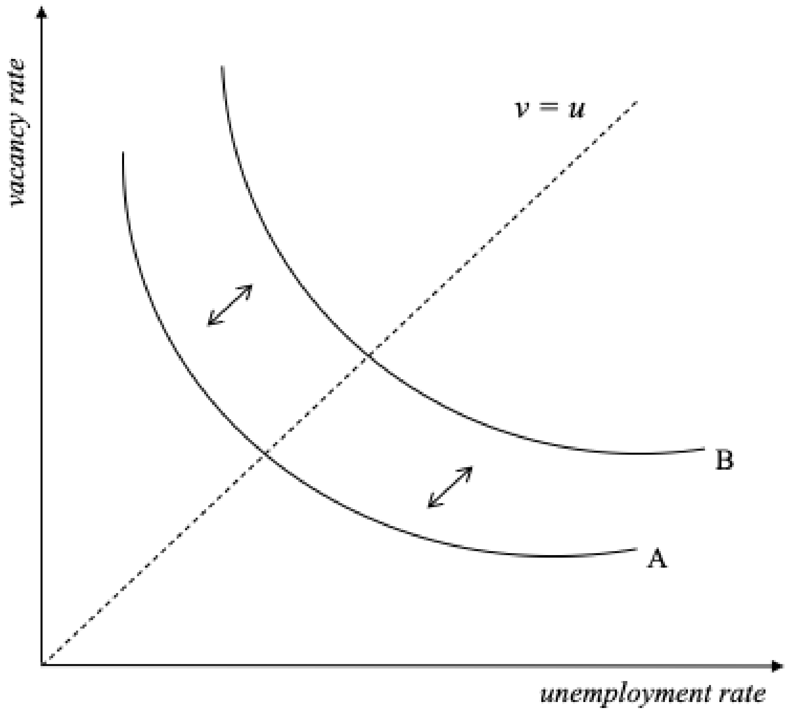
[7] $\gamma \in (0,1)$ and is a measure of congestion in the labor market where and follows the constant returns to scale theory emphasized by Petrongolo and Pissarides (2001).

Figure 2.4. Theoretical Beveridge Curve



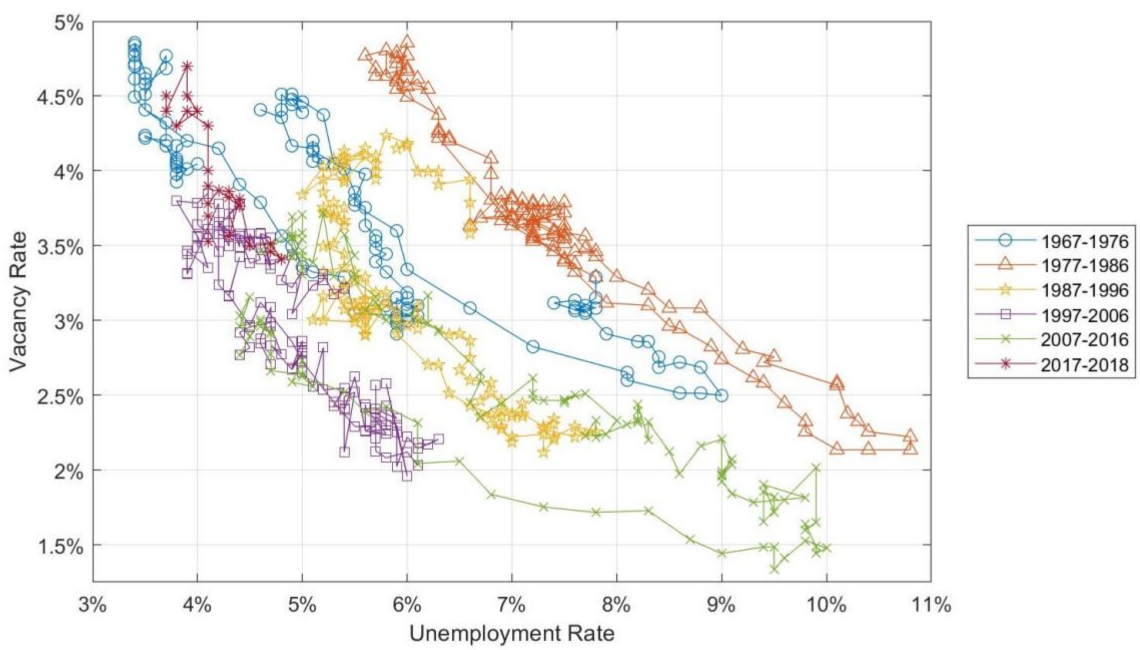
2.3. Empirical Investigation

2.3.1. Empirical Beveridge Curve

To date empirical work has sought to analyze movements in the Beveridge curve (Abraham, 1987; Bleakley and Fuhrer, 1997; Sahin, 2013). However less work has focused on the empirical estimation of matching efficiencies and how successful matches relate to employment (Barnichon and Figura, 2015; Elsby et al., 2015). Since the recession firms are hiring fewer workers even as the unemployment rate is falling. The consequence is that the vacancy rate remains relatively high, and the employment rate is below its pre-recession level. The graphical depiction of these forces is captured in the shift of the Beveridge curve. This can be interpreted as an increase in frictions in the labor market, or a decrease in the matching efficiency (Diamond, 2011; Sahin, 2013; Abraham, 2015).

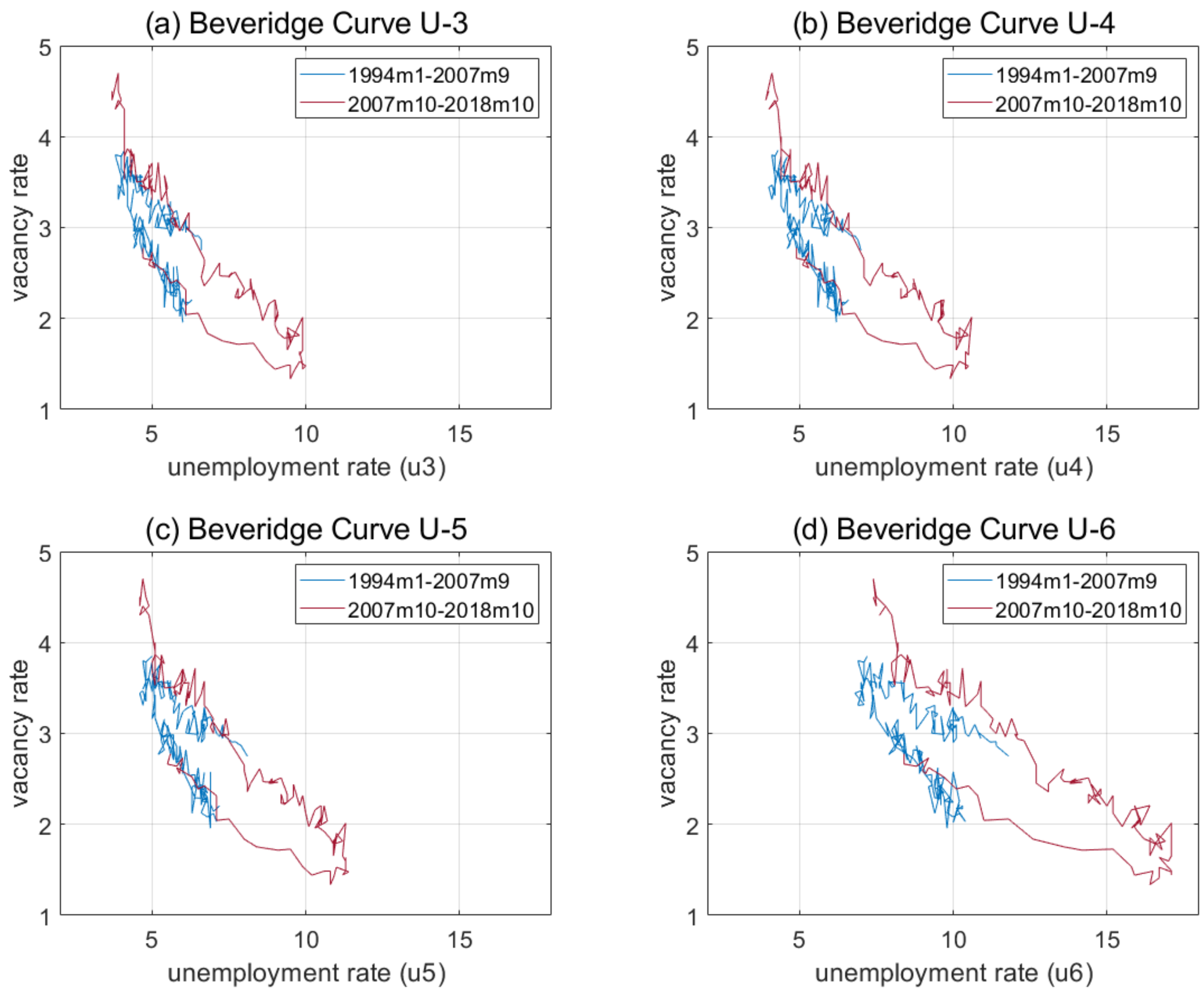
Figure 2.5 depicts the inverse relationship between the unemployment rate and the vacancy rate in a traditional Beveridge curve colored by 10-year intervals. On average, the Beveridge curve is downward sloping such that high vacancy rates are associated with low unemployment rates, reflecting market tightness. In the late 1970's (blue circle) and 1980's (orange triangles), oil shocks were followed by an outward shift in the Beveridge curve (Abraham, 1987; Blanchard and Diamond, 1989). The 2007-2016 period (green x) shows the high levels of unemployment associated with the recession, with low vacancy rates indicating an unprecedented increase in labour market frictions or a decrease in job matching efficiency during the crisis (Diamond, 2011; Sahin, 2013; Abraham, 2015). During the recovery, the Beveridge curve shifted up and outwards once again, with employers posting more job openings but not being able to fill the open vacancies. The continued expansion was followed by a state of high vacancy rates and low unemployment rates as noted in the 2017-2018 period (red asterisk).

Figure 2.5. Beveridge Curve (1967-2018)



As discussed earlier in this paper, different measures of unemployment paint different pictures of the labor force thus have significant implications as to what the "true" level of unemployment is. Therefore, any labor search and match model that does not take account of this variation could over or underestimate the efficiency of the market. We next focus on two sub-periods: 1994m1-2007m9 (blue) and 2007m10-2018m10 (red) for Beveridge curves constructed using different measures of unemployment in Figure 2.6.

Figure 2.6. Beveridge Curve with Different Measures of Unemployment (1994-2018)



In general, we notice a marked contrast between unemployment and vacancy rates in both periods, with job availability being more dispersed in more recent years (vacancy rates between 1.4% and 5.7%, as opposed to 2%-4%). Unemployment rates are also higher during the global financial crisis than the 1994-2007 period, with higher vacancy rates during the recovery years as well. An important takeaway from the Beveridge curves is that the relationship between vacancy and unemployment rates seems to change over time, prompting us to implement dynamic models that can account for heteroskedasticity in the volatility of the series for further analysis.

Another salient feature of the Beveridge curve is that depending on the measure of unemployment used, the extent to which vacancy and unemployment rates relate to one another changes significantly. Comparing the Beveridge curve with U-6, relative to the one with the traditional U-3 measure, not only the right-downward shift during the recession is more pronounced, but also, during the recovery, the left-upward shift remains higher than the 1994-2007 period. Given that as we expand the definition of unemployment, the dynamic with vacancy rates does not change proportionally, accounting for non-linearities to model efficiencies in the job matching process will also be an important feature that we seek to incorporate in our analysis.

2.3.2. Estimating the Matching Function

In this section we estimate the different matching efficiency rates implied by each measure of unemployment. To this end, we build from the seminal Blanchard and Diamond (1989) labor market model to theoretically derive the transition mechanism that takes workers in and out of employment.

Recently empirical work has begun to attempt to estimate a match efficiency parameter whereas early search and match models it was treated as a constant (Barnichon and Figura, 2015;

Crawley and Welch, 2019; Wesselbaum, 2019). To calculate the efficiency, we begin with the matching function.

This paper uses the functional form from Blanchard and Diamond (1989):

(6) $h_t = m_t u_t^{\gamma} v_t^{1-\gamma}$

Where hires (h_t), unemployment (u_t) and the job vacancy rate (v_t), are in rates with respect to the labor force and have a time dynamic. Before calculating the match efficiency parameter, m_t, the degree of congestion, γ, is estimated. This ensures that the matching function follows the constant returns to scale theory advocated by the work of Petrongolo and Pissarides (2001).

The degree of congestion can be a result of the size of the labor market, the geographic location, the diversity of the labor force relative to the diversity of jobs available, the ability of 'outsiders' to compete with 'insiders', and the number of employed seeking job-to-job movements (Dixon et al., 2014).

Much of the matching function literature suggests the parameter chosen for congestion is a rudimentary decision for the researcher based on previous work, a "borrowed parameter" if you will. However, variations in congestion matter (see for example Pissarides, 2000; Shimer and Smith, 2001). Often this value in the United States is between 0.5 and 0.7, with fluctuations being a result of congestion effects (Petrongolo and Pissarides, 2001).

Overall, these externalities arise as the number of job searchers increase. Thus, while the potential number of matches could increase, further frictions arise from the unmatched workers (Dixon et al., 2014). Taking the approach of Dixon et al (2014) this study assumes that the size of the elasticity is inversely related to the severity of congestion externalities in the labor market. In this paper γ is the congestion parameter, where γ = 0 there is complete congestion, while if γ = 1 there is no congestion (Petrongolo and Pissraides, 2001). To find γ, the log of the unemployment rate is regressed on the log of the vacancy rate

(7) $\ln(u_t^i) = \alpha + \beta_i \ln(v_t^i) + \varepsilon_{i,t}$

where $i = \{U3, U4, U5, U6\}$. This regression finds β_i, the elasticity of the unemployment rate to the vacancy rate, which is used to calculate the elasticity of matches to the number of unemployed[8]. This relationship can be expressed as:

(8) $\gamma_i = \frac{1}{1-\beta_i}$

With the estimated congestion parameters, it is now possible to calculate the matching efficiency, m_t. Rearranging equation (6), the matching efficiency for a period can be calculated as:

(9) $m_{i,t} = \frac{h_t}{(u_{i,t})^{\gamma_i},(v_t)^{1-\gamma_i}}$

Using the calculated matching efficiency and analyzing the temporal dynamics, two critical observations can be made. First cyclical trends in the demand for labor maybe captured, the second are the possible early signs of structural disequilibrium in the labor market can be identified.

It is important to note that this parameter is a macroeconomic measure of match efficiency. Changes in direction are more significant than the magnitude. Taking the matching function analysis further, this paper repeats equation (9) to calculate an efficiency parameter for four different classifications of unemployment, U-3, U-4, U-5, and U-6. Acknowledging match frictions in workers who are discouraged, marginally attached, or underemployed, allows for a more complete picture of the market. Summary statistics of the match efficiency calculations as well as the congestion estimates are found in Table 2.2.

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[8] When regressed with lagged u_t and v_t values as instruments, the elasticity changes insignificantly. This result holds in other empirical work as well (e.g. Barnichon and Figura, 2011).

Table 2.2. Match Efficiency and Congestion Results (1994 –2018)

		U-3	U-4	U-5	U-6
(a)					
	γ_i	0.536	0.535	0.555	0.564
	βi	−0.867	−0.869	−0.803	−0.773
		(0.026)	(0.028)	(0.027)	(0.030)
(b) average $m_{i,t}$		0.838	0.816	0.752	0.591
minimum $m_{i,t}$		0.558	0.539	0.503	0.392
maximum $m_{i,t}$		1.057	1.031	0.963	0.774
std. dev. $m_{i,t}$		0.133	0.132	0.122	0.104

Note: Standard errors for β_i coefficients are in parentheses. All estimates are significant at the $p < 0.01$ level.

Looking at Table 2.2, the parameter γ_i presented is the calculated value from equation (8); and these vary little by the measure of unemployment used. However, once the match efficiency is calculated there is significant variation. The official measure of unemployment U-3 has the highest level of efficiency with other measures, notably U-6, showing a greater level of inefficiency. Indeed, the maximum efficiency of M-6 is still lower than the average efficiency of M-3 and M-4. This speaks to the much wider definition of unemployment applied used for U-6.

2.3.3. Business Cycle Turning Algorithm

The contrast in efficiency between different unemployment rates suggest variations in labor market conditions. To further explore this variation, particularly the cyclical component, we turn to the literature as matching efficiencies have a strong link to the business cycle (see for example Boz, et al. 2015; Christiano et al. 2016; Kohlbrecher and Merkl, 2016, Mukoyama et al. 2018).

The cyclical movement of the matching efficiencies could be exploited as a way of capturing temporal discrepancies in our measures. Numerous empirical approaches have been developed to understand the turning points in business cycles and this might now be modified to capture cycles in matching efficiencies.

Harding and Pagan (2002) explored different approaches to identifying the turning points in an economic time-series they classified these techniques as either parametric or non-parametric. This paper introduced the sbbq algorithm to identify local minima (troughs) and local maxima (peaks) in a single time series. Peaks are found where k is larger than k values in both directions and troughs where k values are less than k in both directions. The size of k is set by a censoring rule which from the literature has been defined for a monthly frequency as 5[9].

The censoring rule is required to ensure that each cycle (and each of its phases) have a minimum duration thus a series which exhibits single "blips" are discounted from being wrongly identified. Although to date the sbbq has been used as a means of identifying turns in the business cycle using GDP it also has the potential to capture turning points in other time series.

This work utilizes the sbbq to identify turning points in estimated labor market matching efficiencies (M-3 thru M-6) along-side the employment rate. By comparing the turns in the respective cycles, it is possible to capture which of the matching efficiencies is better correlated with the employment rate. That is to say, which measure better depicts the labor market conditions contributing to matches being made and employment rising. By analyzing this it is also possible to better understand the possible lead these variables might have in explaining future employment.

[9] For more details see the work of Bry and Boschan (1971) and Harding and Pagan (2002).

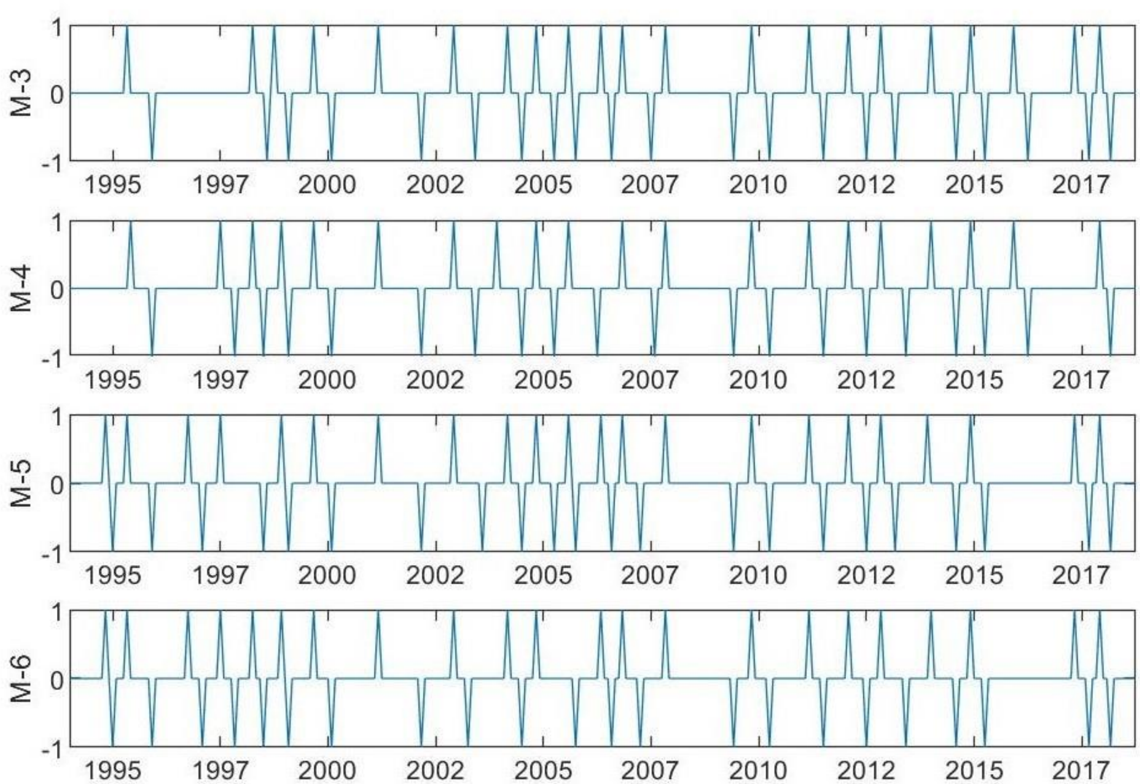
The present work makes use of the Harding and Pagan (2002) approach, cycles are identified according to the requirements in equation (10).

(10) Peak at t if $\{(y_{t-2}, y_{t-2}) < y_t > (y_{t+1}, y_{t+2})\}$

Trough at t if $\{(y_{t-2}, y_{t-2}) < y_t > (y_{t+1}, y_{t+2})\}$

Once the turning points of the cycle have been captured it is possible to describe the characteristics of the cycle in terms of duration, amplitude, steepness, non-linearity, and synchronization with the employment rate. This approach is now applied to our previously calculated matching efficiencies (M-3 thru M-6).

Figure 2.7. Business Cycle Turning Algorithm Results (1994 -2018)



Looking at Figure 2.7, although similar there are variations between each of the efficiencies. Indeed, it suggests that some cycles are moving ahead of others, meaning some of the calculated efficiencies begin to decrease ahead of others. The duration of peaks and troughs is also highly heterogeneous between each. This might suggest a lag or lead component that could be exploited as a labor market indicator. More broadly this suggests very different patterns to the potential labor force.

2.3.4. Correlation to Employment

This work now attends to the central contention set forward at the start of this paper, to assess whether there is a relationship between the matching efficiency and the employment rate.

Initial results from the cycle algorithm reveal the differences between the dynamics of the estimated matching efficiencies using the measures U-3 thru U-6. Therefore, to properly assess the relationship between the matching efficiency and the employment rate each of our measures should be included. To do this we turn to a dynamic from of analysis, the Multivariate Generalized Autoregressive Conditional Heteroskedasticity, MGARCH, model.

Introduced by Engle (2002), the Dynamic Conditional Correlation, a class of the MGARCH models, have the flexibility of univariate GARCH models as well as the parsimonious parametric models used in correlations; all without the complication of the traditional multivariate GARCH. While DCC MGARCH models are not linear, they can be estimated using two-step or univariate methods based on the likelihood function, making them convenient and easy to use with empirical time series (Engle, 2002).

The normality assumption gives rise to the likelihood function, with the model specification presented in matrix notation by Engle (2002) as follows:

(11) $r_t \,|\Im_{(t-1)} \sim N(0, D_t R_t D_t)$

(12) $D_t^2 = diag(\omega_t) + diag(\kappa_i) \circ r_{t-1} r_{t-1}' + diag(\lambda_i) \circ D_{t-1}^2$

(13) $\varepsilon_t = D_t^{-1} r_t$

(14) $Q_t = S \circ (\iota\iota' - A - B) + A \circ \varepsilon_{t-1}\varepsilon_{t-1}' + B \circ Q_{t-1}$

(15) $R_t = diag\{Q_t\}^{-1} Q_t diag\{Q_t\}^{-1}$

Where D_t^2 is the diagonal matrix of conditional variances, Q_t is the dynamic correlation structure, and R_t is the matrix of conditional quasicorrelations as it is neither the unconditional correlation matrix nor the unconditional mean of Q_t, (Aielli, 2013). Also imposed is the constraint that $0 \leq A + B < 1$, thus it must hold that A, B, and $(\iota\iota' - A - B)$ are all positive semidefinite, ensuring Q_t will also be positive semidefinite (Ding and Engle, 2001).

With the above estimator, the log likelihood estimation is as follows:

(16)

$$LL = -\frac{1}{2}\sum_{t=1}^{N}(N\log(2\pi) + 2\log|D_t| + r_t' D_t^{-1} D_t^{-1} r_t - \varepsilon_t'\varepsilon_t + \log|R_t| + \varepsilon_t' R_t^{-1}\varepsilon_t)$$

Letting the parameters in D be denoted by θ and the additional parameters in R be denoted by ϕ allows the log likelihood to be split up into two parts, one for the volatility and one for the correlation (Engle, 2002).

(17) $LL(\theta, \phi) = L_v\,(\theta) + L_c\,(\theta, \phi)$

(18) $L_v(\theta) = -\frac{1}{2}\sum_{t=1}^{N}(N\log(2\pi) + 2\log|D_t| + r_t' D_t^{-2} r_t)$

(19) $L_c(\theta, \phi) = -\frac{1}{2}\sum_{t=1}^{N}(\log|R_t| + \varepsilon_t' R_t^{-1}\varepsilon_t - \varepsilon_t'\varepsilon_t)$

(20)

Thus, it yields the two-step approach to estimating the log likelihood.

The first step is to solve:

(21) $\hat{\theta} = \text{argmax}\{L_v(\theta)\}$

The second step is to use the result above to find:

(22) $\max_{\phi}\{L_c(\hat{\theta}, \phi)\}$

Consistency of the first step ensures consistency of the second, hence under reasonable conditions the model is consistent (Engle, 2002). While the dynamic conditional correlation is not common in empirical literature surrounding the labor market, it is critical in this analysis as it focuses on the varying movements in the respective match efficiencies across time.

Often found in empirical work in financial markets (Bauwens et al., 2006), the DCC MGARCH helps empirically estimate optimal hedge strategies, asset allocations, as well as correlations between interest rates and other critical economic variables such as oil prices, stock indexes and exchange rates (Bautista, 2003; Ledoit et al., 2003). The dynamic conditional correlation has also found its way into other strands of the literature. Chevallier (2016) uses this method to consider the time-varying correlations between oil prices and CO2 prices as well as gas prices and CO2 prices, and notes the usefulness of this form of model for applied economics in general.

2.4. Results and Discussion

The MGARCH model is run three times each with multiple lags on the efficiencies. First it is run for the entire time period, 1994-2018, second for before the great recession, 1994-2007, and third for during and after the recession, 2008-2018. Dynamic correlations are reported for the selected matching efficiencies and the employment rate in Table 2.3.

Table 2.3. DCC MGARCH Results

Correlation Between Employment and:

	M-3	M-4	M-5	M-6
(a) 1994-2018				
4 lags	0.7454	0.7367	0.7411	0.7169
	(0.0685)	(0.0693)	(0.0691)	(0.0717)
5 lags	0.6959	0.6885	0.7012	0.6920
	(0.1212)	(0.1212)	(0.1211)	(0.1216)
6 lags	0.7397	0.7316	0.7373	0.7209
	(0.0719)	(0.0731)	(0.0729)	(0.0754)
(b) 1994-2007				
4 lags	0.5187	0.5316	0.5081	0.5098
	(0.0748)	(0.0731)	(0.0769)	(0.0770)
5 lags	0.5472	0.5687	0.5482	0.5369
	(0.0745)	(0.0719)	(0.0762)	(0.0780)
6 lags	0.5571	0.5616	0.5427	0.5504
	(0.0788)	(0.0773)	(0.0819)	(0.0826)
(c) 2008-2018				
4 lags	0.5450	0.5383	0.5281	0.6000
	(0.1275)	(0.1303)	(0.1344)	(0.1179)
5 lags	0.6569	0.6628	0.6422	0.7014
	(0.0836)	(0.0829)	(0.0868)	(0.0746)
6 lags	0.7565	0.7623	0.7495	0.7902
	(0.0618)	(0.0809)	(0.0637)	(0.0563)

Note: Standard errors on correlation coefficients are in parentheses. All correlations are significant at the p<0.01 level.

Panel (a) shows the results for the entire time period. The high conditional correlation (0.69-0.75) between the standardized residuals of employment and matching efficiency rates suggests that regardless of the definition of unemployment, the job matching efficiency of the labor market is, on average, positively and highly connected to employment dynamics.

Panel (b), however, indicates that during the 1994-2007 subperiod, the overall correlation between employment and matching rates was more muted, between 0.51 and 0.56, depending on the model specification. During this time, the M-4 estimated matching efficiency had the highest correlation to the employment rate, regardless of the number of lags used in the estimation of the parameters. This makes intuitive sense as U-4 contains discouraged workers able to re-enter the labour force only after matching with a job vacancy; whereas U-3 contains only those who would remain in the labor force as unemployed.

The key finding is in Panel (c); that the most highly correlated measure after the recession is M-6 a measure that includes underemployment. The work of Bell and Blanchflower (2018) speak at length regarding the importance of recognizing underemployment and, for the first time, this present paper highlights empirically how it is strongly correlated to the employment rate. Our results provide empirical evidence that measures of underemployment, specifically those that include part-time workers for economic reasons, have become more representative of labour market dynamics in the U.S. over the past decade. This in turn would lead one to question whether U-3 is the most appropriate value to use when discussing the current US labor market.

2.5. Conclusion

This paper fills a gap in the literature by providing the first empirical correlations between the matching efficiency and the employment rate. We analyze labour market data and estimate matching efficiency rates by using different measures of unemployment. We identify that labour market dynamics post global financial crisis are associated with a slower rate of growth in the matching efficiency of unemployed workers to jobs. In particular, including part-time workers for economic reasons (to capture underemployment levels) allows for frictions in the job matching process to better describe the labour market dynamics observed throughout the latest expansionary period. Our findings suggest that changes in the labour market at the intensive margin are more important than they used to in explaining employment dynamics.

One area for future development is to relate our work to wage growth post financial crisis. Traditional theory would suggest that as the level of unemployment falls, the number of available workers decreases, and the equilibrium wage rate rises, to see workers take up employment (Phelps, 1968). In the present U.S. economy, however, wage rates have remained static at a time of falling numbers in the labour force, suggesting that the matching process may be less efficient (Crawley and Welch, 2019).

CHAPTER 3

IS LABOR MATCHING EFFICIENCY AN INCIDATOR OF OUTPUT? A NEW INVESTIGATION OF COMPOSITE INDICES

3.1. Introduction

This paper poses a new composite economic index augmenting previous approaches used prior to the great recession; following the style of the coincident economic index and leading economic index from Stock and Watson (1989). Since 2009, many critical aspects of the economy have changed; from interest rates near the zero-lower bound, record low levels of unemployment, falling labor force participation, and stagnant inflation and wages. Due to these changes, some of the canonical variables previously used as economic indicators are becoming less consistent (see for example Bognanni 2019; Kiley, 2018).

The yield curve became a mainstream predictor of economic recessions in the United States in the mid 1990's following the work of Campbell (1995), Haubrich and Dombrosky (1996), Estrella and Mishkin (1998), and Dueker (1997). The yield spread already appeared in many macroeconomic models and indices before this time, but an inversion of the curve became indicative of a looming recession. While the yield curve is still a useful indicator, quantitative easing may have an adverse effect on the predictive power (Baumeister and Benati, 2010). This paper seeks to find indicators that perform well before, during, and after the recession. Following the results from Chapter 2, a new indicator is proposed that captures the efficiency of the labor market, thus allowing dynamics from the real economy to bring new insights.

The first section of the paper describes the background of composite indices and some critiques as well as support of their use. The second section describes the overall methods of creating the indices, which involve variable selection, normalization, and the weighting of indicators. The third describes each variable used in the indices and the economic intuition behind them. The fourth section presents results of the coincident, leading, and composite indices. The final section is a discussion of the indices and describes future work.

3.2. Background

A composite index is a unitless aggregation of variables, known as indicators, that are used to estimate cohesive movements in the economy. Composite indices are widely used across economics from social wellbeing or poverty (Anand and Sen, 1994; Sharpe, 1999) sustainability performance of an industry (Moldan et al., 2004; Singh et al., 2007) or an index that measures environmental change (des Neves Almeida et al., 2017). However, the most popular uses of composite indices in economics are to analyze the business cycle (Hertzberg et al., 1998; Filardo and Gordon, 1998), forecast output (Diebold and Rudebusch, 1991), and specify recession probabilities (Stock and Watson, 1989).

Indicators used in an index are either leading, lagging, or coincident. Lead indicators are used for prediction of movements in the greater economy as they often move ahead of the business cycle. As discussed earlier, an example of a leading indicator is the yield curve (Campbell, 1995, Dueker, 1997). Lag variables are the opposite and will change direction after a change in the greater economy. Examples of lagging indicators are duration of unemployment or the consumer price index for services (Conference Board, 2001). Coincident indicators fall in the middle as their movements coincide with changes in the aggregate economy. Common coincident indicators used are measures of production and employment (Stock and Watson, 1989).

The aggregate nature and subjectivity of composite indicators has led many to criticize the metric. It has been noted that the index could send misleading messages if it is poorly constructed (Saisana and Tarantola, 2002; Saltelli et al., 2005) and thus the methodology has come under scrutiny from variable selection to weighting and construction. The researcher needs to be transparent of their methods and base their decisions on sound statistical principles. Despite the critiques, there is support for composite indices. Saisana and Tarantola, (2002) and Saltelli et al. (2005) note their ability to summarize complex and multi-dimensional issues in one aggregate format that allows policymakers and the public to easily digest what is occurring in the world around them.

A composite economic index does not have the robustness of other models used for economic forecasting, such the Dynamic Stochastic General Equilibrium (DSGE) model which has dominated economic forecasting by central banks (Tovar, 2009; Christiano et al. 2018). However, this may not be a negative factor as there have been extensive critiques on the DSGE methodology since the great recession (Canova and Sala, 2009; Blanchard, 2016; Linde, 2018; Stiglitz, 2018).

Over the last decade, there have been many critiques of macroeconomic modeling, many of which lie within identification issues and imaginary shocks (Romer, 2016). Increasing the number of variables in complex models like DSGE creates a major identification problem and allows for the results to lie upon the econometrician rather than the actual data (Canova and Sala, 2009; Iskrev, 2010; Nakamura and Steinsson, 2018). Similarly, many macroeconomists have attributed changes in aggregate variables to imaginary shocks rather than fluctuations caused by real activity in the economy (Romer, 2016). Therefore, it is important to have empirical data to observe and analyze while the convoluted nature of macroeconomic models is under debate. A composite macroeconomic index is not an overcomplicated technique trying to explain changes in the economy. This paper seeks to build an index of coincident and leading macroeconomic variables for the purpose of analyzing the current economic conditions.

3.3. Methods

The earliest work that focused on economic indicators to measure activity began with Mitchell and Burns (1938). In an NBER volume they discuss a collection of leading, lagging, and coincident indicators for the United States. Mitchell and Burns (1938) posit that the ideal indicator should have a number of distinct properties:

- Span enough time to cover a variety of business cycle conditions
- Lead a cyclical change by at least three months
- Show no erratic movement in the middle of the cycle,
- Move in a clear direction that is easily picked up
- Be related to the business activity enough so that its future behavior should exhibit past behavior

To find all these properties in an indicator is challenging, and Mitchell and Burns (1938) admit that the selection of variables is cumbersome and requires subjective judgement by the researcher.

The seminal work of Stock and Watson (1989) create new indices of coincident and leading indicators for an academic audience following the influence of Mitchell and Burns (1938). They provide a mathematical foundation for the notions of a reference cycle and a leading cycle and propose a list of variables that make up the best coincident and leading indices. There are varying methods across the literature to construct indicators, some more complex while others are purely data driven.

This paper uses the guidelines presented by Mazziotta and Pareto (2013) and Saisana and Tarantola (2002) to construct three indices: a coincident economic index (CEI), a leading economic index (LEI), and a composite index that combines indicators from the leading and coincident indices. The first step is to determine the indicators used in the indices, the second is to normalize the indicators, and the third is to construct the final indices.

3.3.1. Variable Selection

The first step of constructing the composite index is to determine which variables to use as economic indicators. Adopting the indicators and approach of Stock and Watson (1989) as well as borrowing new indicators from the dynamic probit literature (Kauppi and Saikkonen, 2008; Nyberg, 2010; Ng, 2012) this work begins to construct a new index. The potential variables are listed in Table 3.1[10].

The data for each indicator is collected monthly from 1994[11] thru 2019. The original sources for variables include the Bureau of Labor Statistics, Federal Reserve System, Bureau of Economic Analysis, Census Bureau, and the United States Treasury Department. Specific sources of data for each coincident and leading indicator are discussed in sections 3.4.1 and 3.4.2 respectively.

[10] Many of the variables are used as indicators by multiple economists; however, for the purposes of space only one reference is listed for each variable.
[11] The data used for the matching efficiency, the indicator of focus, is only available beginning in January 1994.

Table 3.1. All Variables Considered

Indicator	Variable Type	Index Tested	Used By
Industrial Production	Level Percent Change	CEI, LEI	Stock and Watson (1989)
Personal Income	Level Percent Change	CEI, LEI	Stock and Watson (1989)
Manufacturing Sales	Level Percent Change	CEI	Stock and Watson (1989)
Employment Rate	Level Percent Change	CEI	Stock and Watson (1989)
Private vs Public Rate	Level	CEI, LEI	Stock and Watson (1989)
Building Permits	Level Percent Change	LEI	Stock and Watson (1989)
Unfilled Orders	Level Percent Change	LEI	Stock and Watson (1989)
Trade Exchange Rate	Level Percent Change	LEI	Stock and Watson (1989)
Part Time Work	Level Percent Change	CEI, LEI	Stock and Watson (1989)
10-Year T-Bond Yield	Level Difference	LEI	Stock and Watson (1989)
S&P 500	Level Percent Change	LEI	Stock and Watson (1989)
Equity Price Index	Level Percent Change	LEI	Ng (2012)
House Price Index	Level Percent Change	LEI	Ng (2012)
Yield Spread	Level	LEI	Stock and Watson (1989)
Ted Spread	Level	LEI	Ng (2012)
Retail Sales	Level Percent Change	CEI, LEI	Mitchell et al. (2005)
Match Efficiency (M3)	Level	LEI	From Chapter 2
Match Efficiency (M4)	Level	LEI	From Chapter 2
Match Efficiency (M5)	Level	LEI	From Chapter 2
Match Efficiency (M6)	Level	LEI	From Chapter 2

To begin variable selection, each potential variable is correlated with the binary NBER recession indicator converted into months. The correlations were done with a varying lag structure of 0 lags, 1 lag, 3 lags, 6 lags, 9 lags, and 12 lags. These lag lengths are based on selections used by Stock and Watson (1989) in their indices as well as lag selection methods in the dynamic probit literature (Ng, 2012). Summary statistics are collected for each potential variable as well, and any variables that were excessively noisy[12] are smoothed by using a moving average smoother with the optimal lag selection. Finally, each potential variable for the CEI and LEI are correlated with each other to avoid issues of multicollinearity and minimize redundancy (Salzman, 2003; Mazziotta and Pareto, 2013).

The next step in determining variable selection is to run probability models with the binary recession indicator as the dependent variable to test which combination of independent variables yields the best model fit (Kauppi and Saikkonen, 2008; Ng, 2012). Stock and Watson (1989) warn about the issue of overfitting the data when constructing composite indices, and that fewer explanatory variables is preferred to every variable being in the model. The proposed idea with using the probability model as a selection mechanism is that the combination of variables that yield the best model would also yield the most accurate composite index. The model was selected based on the pseudo R-squared, AIC, and BIC criterion as well as significance of the independent variables.

[12] Determined by observations of the variable as well as recommendation from Stock and Watson (1989).

3.3.2. Probit Model

The binary recession indicator is defined as[13]:

$$(1)\ y_t = \begin{cases} 1, \text{if the economy is in a recessionary state at time } t \\ 0, \text{if the economy is not in a recessionary state at time } t \end{cases}$$

Conditional on the information set Ω_{t-1}, the recession indicator, y_t, has a conditional Bernoulli distribution

$$(2)\ y_t|\Omega_{t-1} \sim B(p_t)$$

Given the conditional expectation, $E_{t-1}(\cdot)$, and the conditional probability, $P_{t-1}(\cdot)$, for the information set Ω_{t-1}, p_t is the conditional probability that $y_t = 1$.

$$(3)\ E_{t-1}(y_t) = P_{t-1}(y_t = 1) = \Phi(\pi_t) = p_t$$

The link function between the conditional probability, p_t, and the model equation π_t, a linear function of explanatory variables, is a standard normal distribution $\Phi(\cdot)$. Therefore, the "static" probit model with lags of explanatory variables is as follows:

$$(4)\quad \pi_t = \omega + \boldsymbol{x}'_{\boldsymbol{t-k}}\boldsymbol{\beta}$$

Where all explanatory variables are included in the vector $\boldsymbol{x}_{\boldsymbol{t-k}}$, and k represents the lag length on individual variables within the vector. This static probit model is commonly used in forecasting recessions see for example the work of Estrella and Mishkin (1998) and Bernard and Gerlach (1998). Although, there is a critique that this method can be flawed due to misspecification based on the autocorrelation structure (Dueker, 1997; Nyberg, 2010).

To try and mitigate this issue, the dynamic probit suggested by Dueker (1997), Kauppi and Saikkonen (2008), and Nyberg (2010) is similar to equation 4 above but includes a lagged value of the dependent variable on the right-hand side. Equation 5 shows the updated linear model.

---

13 Notation from Nyberg (2010).

(5) $\pi_t = \omega + \delta_1 y_{t-1} + \boldsymbol{x}'_{\boldsymbol{t-k}}\boldsymbol{\beta}$

The dynamic model (5) was initially used for testing the variable specification in the LEI. However, using the lagged dependent variable in the model resulted in overspecification. In this paper the probability model is not being used for forecasting, but rather to show overall fit. Therefore, the simplified "static" model in (4) is sufficient.

When running the models for the CEI, the lag length k is equal to 0. For the LEI, the preliminary lag length used on variables was selected based on the individual correlations with the binary recession indicator.

(6) $y_t = \beta_0 + \beta_1 IND\_PRO_t + \beta_2 MFG\_SALES_t + \beta_3 PTFER_t + \beta_4 CP6\_TR6_t$

(7) $y_t = \beta_0 + \beta_1 INC\_LTP_{t-3} + \beta_2 MUO_{t-6} + \beta_3 YTB\_10_{t-3} + \beta_4 SP\_500_{t-3} + \beta_5 PERMIT_t + \beta_6 RETAIL\_SALES_{t-1} + \beta_7 YIELD\_SPREAD_{t-6} + \beta_8 TED\_SPREAD_{t-3} + \beta_9 M\_6_{t-12}$

The results for the optimal models in the equations (6) and (7) can be found in Tables 2 and 3 respectively.

Table 3.2. Probit Model for Coincident Economic Indicators

Variable	Parameter Estimate	Avg Marginal Effects
IND_PRO	-2.0283***	-0.0862***
	(0.4901)	
MFG_SALES	-0.4456*	-0.0189*
	(0.2583)	
PTFER	0.3187**	0.0315**
	(0.1344)	
CP6_TR6	3.9576***	0.1682***
	(0.8433)	
Constant	-4.4277***	
	(0.7095)	
N	308	
Log Likelihood	-24.1865	
Pseudo R^2	0.7541	
AIC	58.3730	
BIC	77.0235	

*Note: Standard errors on the parameter estimates are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

Table 3.3. Probit Model for Leading Economic Indicators

Variable	Lag	Parameter Estimate	Avg Marginal Effects
INC_LTP	3	-2.3145*** (0.8438)	-0.0458***
MUO	6	-1.2564* (0.7005)	-0.0249**
YTB_10	3	-4.5114** (2.2191)	-0.0894**
SP_500	3	-0.2688** (0.1346)	-0.0053**
PERMIT	0	-0.0134*** (0.0045)	-0.0027***
RETAIL_SALES	1	-0.7437 (0.5159)	-0.0147
YIELD_SPREAD	6	-3.1966*** (1.2414)	-0.0633***
TED_SPREAD	3	3.6848* (2.0248)	0.0730**
M_6	12	44.8752*** (15.4177)	0.8886***
Constant	--	-13.5476** (6.6825)	
N		299	
Log Likelihood		-10.8430	
Pseudo R^2		0.8887	
AIC		41.6861	
BIC		78.6905	

*Note: Standard errors on the parameter estimates are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

3.3.3. Normalizing Variables and Index Construction

Before constructing the index, it is necessary to ensure that the directional effect from all variables is the same. This way, an increase in the indicator creates an increase in the composite index (Mazziotta and Pareto, 2013). Since the binary recession indicator is a 1 for a recession, the desired correlation, or parameter value, between the normalized indicators and the recessionary variable is negative. Therefore, an increase in an indicator increases the index, which, ceteris paribus, decreases the likelihood of a recession.

Before any aggregation, it is important to transform the indicator into a pure, dimensionless, number to ensure the variables are comparable. There are a variety of methods to do this, but a common method in the literature is re-scaling the variables using a min-max transformation which normalizes the variables to values between 0 and 1, inclusive (Mazziotta and Pareto, 2013).

(8) $X' = {}^{X\ - X_{min}}/_{X_{max} - X_{min}}$

Once every variable is normalized using equation 6, the next step is weighting the variables for aggregation into the composite index. There is not a universal consensus on composite index construction and methods of aggregation can be simple to highly complex. The simplest method of aggregation is equal weights, this is commonly done first to minimize placing undue weight on certain variables (Mazziotta and Pareto, 2013).

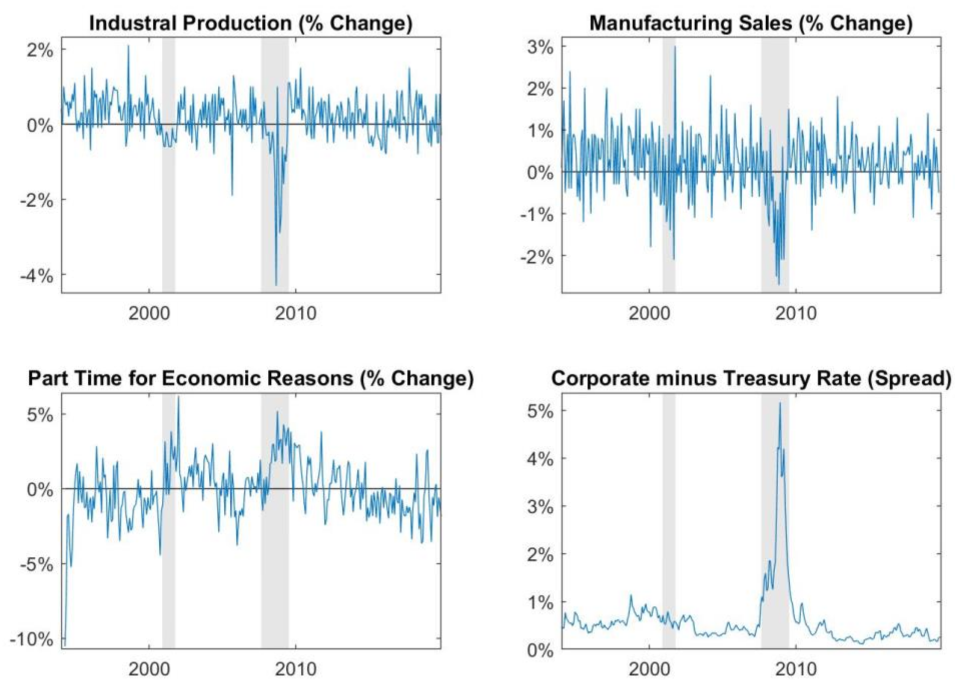
Alternatively, weights can be subjective and determined by policymakers on what they believe is most important. A third multivariate method is an objective weighting from a Principal Component Analysis, which computes eigenvectors and eigenvalues from a covariance matrix of indicators to produce the principal components and are then used to determine the indicator weights and aggregation of the index (Mazziotta and Pareto, 2013). For the purpose of this preliminary investigation, the method of aggregation uses equal weights, following the suggestion of Mazziotta and Pareto (2013). The final indices are then smoothed[14] to remove excess volatility.

3.4. Description of Variables

3.4.1. Coincident Economic Index

The following are descriptions of the variables used in the CEI. Figures of all coincident variables used are found in Figure 3.1. A table of summary statistics and correlations to the binary recession indicator are found in Table 4.

Figure 3.1. Coincident Indicators



14 Lag lengths were tested for the moving average smoother. The optimal lag length for both indices is 3 months.

Table 3.4. Summary Statistics and Correlations for CEI Variables

Variable	IND_PRO	MFG_SALES	PTFER	CP6_TR6
Type	Percent Change	Percent Change	Percent Change	Level
Time	1994m1 - 2019m12	1994m1 - 2019m10	1994m3 - 2019m12	1994m1 - 2019m12
Mean	0.153	0.219	-0.150	0.592
Standard Deviation	0.645	0.773	2.101	0.627
Minimum	-4.300	-2.700	-15.850	0.110
Maximum	2.100	3.000	6.225	5.160
Correlation to Recession	**-0.457**	**-0.361**	**0.361**	**0.678**
Correlation Lag 1	-0.441	-0.321	0.312	0.667
Correlation Lag 3	-0.402	-0.341	0.200	0.597
Correlation Lag 6	-0.290	-0.253	0.110	0.422
Correlation Lag 9	-0.186	-0.158	0.016	0.215
Correlation Lag 12	-0.046	-0.051	0.030	0.127

Industrial Production Index (IND_PRO, 1994m1 – 2019m12)

The industrial production index measures real output for manufacturing, mining, electric, and gas utilities facilities located in the United States as determined by NAICS codes. This indicator highlights structural developments in the economy and allows for movements in production output to be observed. Therefore, it is not surprising that it has a negative correlation and effect on the binary recession indicator as an increase in the growth rate of the index signals that a recession is less likely. The data on the industrial production index is seasonally adjusted and is from the Federal Reserve System Board of Governors and is converted into a percentage change for this analysis.

Manufacturing and Trade Sales (MFG_SALES, 1994m1 – 2019m10)

This data on manufacturing and trade sales is constructed by the Federal Reserve Bank of St. Louis. Manufacturing and trade sales are seasonally adjusted and level units are in 2012 chained dollars. For this analysis, the percent change is used, following the approach of Stock and Watson (1989). There is a negative correlation between this indicator and the binary recession indicator as seen in Table 4. From the probit model results in Table 2, it is also clear that an increase in the growth rate of manufacturing and trade sales decreases the likelihood of a recession. This makes intuitive sense as strong manufacturing often signals a strong economy.

Part Time for Economic Reasons (PTFER, 1994m3 – 2019m12)

The data for change (%) in the level of part time for economic reasons is from the Bureau of Labor Statistics Current Population Survey. This definition represents individuals who are working part time but would like to work full time, another common description of this classification of workers is underemployed. Bell and Blanchflower (2018) discuss the issues that underemployment has on the labor market and the economy as a whole. From the results of the correlations and the probit model, an increase in the growth rate of workers who are part time for economic reasons increases the likelihood of a recession.

It is important to note that Stock and Watson (1989) use this in their leading index to represent labor market slack; however, from the correlations in Table 4 it is clear that for the time period of 1994 through 2019, this is a coincident indicator. Paper 1 of this thesis shows that the labor match efficiency most correlated, to the unemployment rate that included workers who were part time for economic reasons, U-6, following the 2008 recession. These results suggest that the dynamics of the labor market has changed. Therefore, this present paper uses the growth rate of part time for economic reasons in place of the employment rate and employee hours worked which were originally suggested for use in the coincident index by Stock and Watson (1989).

6-Month Corporate vs Treasury Spread (6CP_6TR, 1994m1 – 2019m12)

This spread is measured as the 6-month High Quality Market (HQM) corporate bond spot rate minus the 6-month Treasury Constant Maturity rate. The HQM methodology computes spot rates based on data from high quality corporate bonds rated AAA, AA, and A. The HQM data is from the U.S. Department of the Treasury and the 6-month treasury data is from the Federal Reserve Board of Governors. This treasury rate data is published daily but can be extracted monthly from FRED using an average aggregation method.

This variable is used in Stock and Watson (1989) as a leading indicator, however over this time frame it is a coincident indicator. It is important to note that the data collected for use in this index begins in 1994, after Stock and Watson (1989) published their seminal paper, so is not surprising that some lag specifications have changed. In terms of effects, an increase in the spread of corporate rates to treasury rates increases the likelihood of a recession.

3.4.2. Leading Economic Index

The following are descriptions of the variables used in the LEI. Figures for all coincident indicators can be found in Figure 3.2 and a table of summary statistics and correlation to the binary recession indicator for all coincident variables used can be found in Table 3.5.

Figure 3.2. Leading Indicators

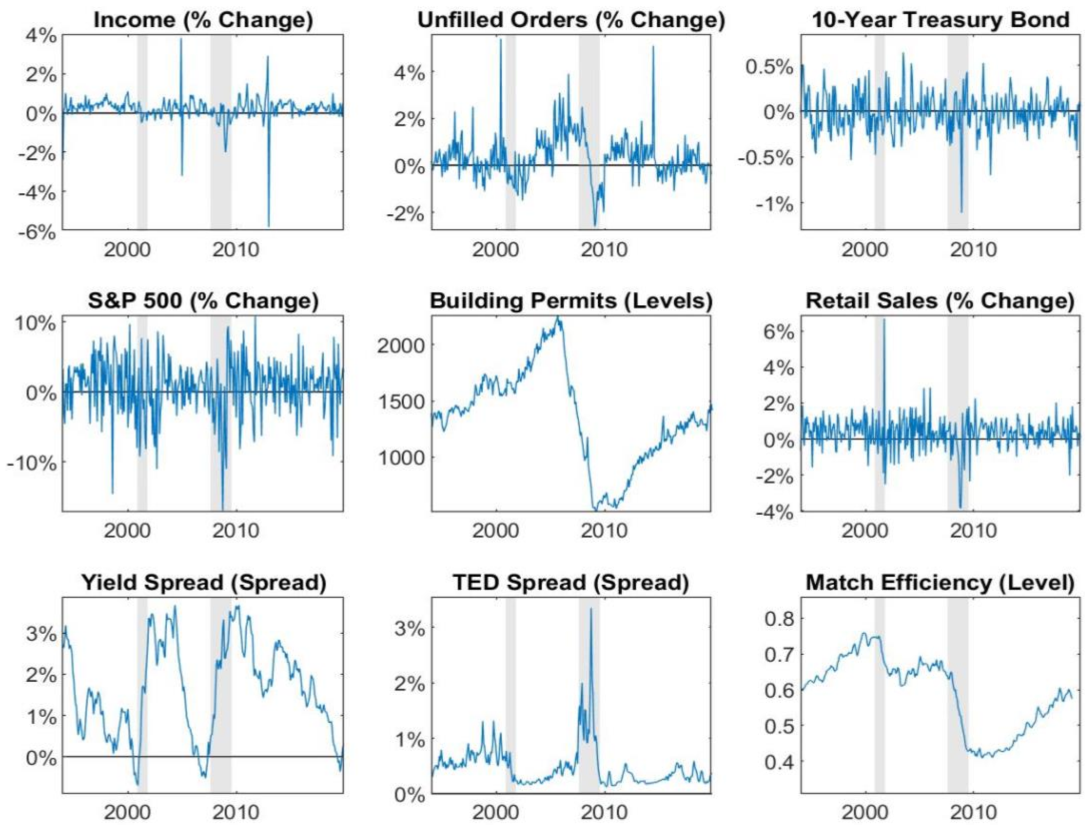


Table 3.5. Summary Statistics and Correlations for LEI Variables

Variable	INC_LTP	MUO	YTB_10	SP_500	PERMIT
Type	% Change	% Change	Differences	% Change	Level
Time	1994m1 - 2019m11	1994m1 - 2019m11	1994m1 - 2019m12	1994m1 - 2019m12	1994m1 - 2019m12
Mean	0.212	0.324	-0.013	0.710	1349.865
Standard Dev.	0.631	0.962	0.217	4.159	429.651
Minimum	-5.800	-2.600	-1.110	-16.942	513.000
Maximum	3.800	5.400	0.641	10.772	2263.000
Correlation to Recession	-0.224	-0.192	-0.037	-0.239	**-0.206**
Lag 1	-0.221	-0.153	-0.079	-0.206	-0.190
Lag 3	**-0.227**	-0.059	-0.115	**-0.250**	-0.149
Lag 6	-0.112	0.098	**-0.148**	-0.224	-0.087
Lag 9	-0.094	0.254	-0.077	-0.136	-0.021
Lag 12	-0.031	**0.310**	-0.041	-0.063	0.042

Variable	RETAIL_SALES	YIELD_SPREAD	TED_SPREAD	M_6
Type	% Change	Level	Level	Level
Time	1994m1 - 2019m12	1994m1 - 2019m12	1994m1 - 2019m12	1994m2 - 2018m12
Mean	0.339	1.637	0.475	0.590
Standard Dev.	0.949	1.117	0.363	0.103
Minimum	-3.900	-0.700	0.120	0.409
Maximum	6.700	3.680	3.350	0.759
Correlation to Recession	-0.216	0.089	0.549	0.046
Lag 1	-0.211	0.030	0.595	0.073
Lag 3	**-0.228**	-0.074	**0.625**	0.124
Lag 6	-0.217	-0.217	0.602	0.180
Lag 9	-0.102	-0.324	0.451	0.222
Lag 12	-0.027	**-0.374**	0.357	**0.256**

Income Less Transfer Payments (INC_LTP, 1994m1 – 2019m11)

This indictor is real personal income excluding current transfer receipts measured in billions of chained 2012 dollars and seasonally adjusted at an annual rate. The data is from the Bureau of Economic Analysis and is extracted in percent change, following the approach of Stock and Watson (1989). Income is one of the most important indicators when discussing economic activity, and it is negatively correlated with and has a negative effect on the binary recession indicator. The interpretation being that an increase in the income growth rate, lagged 3 months, decreases the likelihood of a recession.

Manufacturing Unfilled Orders (MUO, 1994m1 – 2019m11)

In addition to manufacturing sales in the coincident index, the percent change of manufacturer's unfilled orders for durable goods industries in the leading index. The data is from the Census Bureau. In the index a 6-month lag[15] of manufacturer's unfilled orders is used, making it one of the variables with a greater lead.

The implication of unfilled orders is mixed from analyzing the correlations alone; however, the leading probit shows that an increase in the lagged percent change of manufacturing unfilled orders decreases the likelihood of a recession. These results follow the intuition of Zarnowitz (1962), that large fluctuations in unfilled orders reflect the tendency for average delivery periods to become longer during expansions and shorter during contractions. In periods of excess demand, unfilled orders will accumulate and likewise a decline in unfilled orders is not a good sign (Barker, 2011).

[15] This was originally at a 12-month lag however the model increased in goodness of fit after changing it to a 6-month lag. Justification for this shown in Appendix B Model 2.

Yield on 10-year Treasury Bond (YTB_10, 1994m1 – 2019m12)

This difference from period to period of the 10-year United States Treasury Bond is used as longer term interest rates provide insight in evaluating future expectations for the economy and reactions to changes in short term rates (Campbell, 1995). Movements in long term rates are also important to observe during the time frame in this paper as the federal funds rate has been at the zero-lower bound for a portion of the time period (Wright, 2012; Hördahl et al., 2016).

The 3-month lag of the differences in the 10-year treasury bond is used in the index and the data is from the Federal Reserve Board of Governors. Following economic intuition, the leading probit model shows that an increase in the lagged difference decreases the likelihood of a recession.

S&P 500 (SP_500, 1994m1 – 2019m12)

Including the growth rate of the S&P 500 in the leading index is useful, as it adds the behavior of equity markets to the other indicators which measure the real economy (Fama, 1981). Although Stock and Watson (1989) exclude the S&P 500 from their index, they note the predictive power of equity markets. More recent work includes stock prices, such as Ng (2012) who uses the S&P 500 (deflated by the CPI) in a dynamic probit forecasting model. The equity price index was tested as a potential variable to include in the leading economic index constructed in this paper but did not perform as well as the S&P 500 growth rates.

The historic S&P 500 data is extracted from Yahoo Finance and monthly estimates are calculated by an average of the opening values. For the index this series is lagged by three months, and an increase in the lagged growth rate has a negative effect on the likelihood for a recession based on the results from the probit model.

Building Permits (PERMIT, 1994m1 – 2019m12)

New private housing units authorized is captured by building permits data is extracted from the Census Bureau in thousands of units and seasonally adjusted at an annual rate. Unlike many of the other variables in the composite and leading index, the data for building permits used are in levels. This is possible as there is not an autoregressive nature to the series.

This paper, following the work of Ng (2012), used a housing price index but after testing it was found that the lagged building permits data did not have a higher correlation to the binary recession indicator. Using permits increased the fit substantially in the leading probit compared to the housing price index[16]. In addition, adding permits to the composite probit in equation 6 decreased the goodness of fit of the model. Overall, the idea that an increase in building permits decreases the likelihood of a recession makes intuitive sense.

Retail Sales (RETAIL_SALES, 1994m1 – 2019m12)

Most recent month's advanced estimate of total sales for retail and food services is based on data from a subsample of firms from the larger Monthly Retail Trade Survey from the Census Bureau. The data is in percent change in millions of dollars and is seasonally adjusted. The lagged value of the percent change in retail sales is negatively correlated with the binary recession indicator. However, in the leading probit model retail sales are not statistically significant.

Even though lagged retail sales are not significant at the 10% level, this indicator represents consumption, making up approximately 70% of output in the US and has been used as a proxy of monthly economic activity in the past (Mitchell et al., 2005). Hence, we believe it is a useful addition to the model. Once included the goodness of fit on the leading probit model increases[17].

16 See Appendix B Model 3 for justification.

17 Justification is found in the Appendix B Model 4.

10-Year minus 3-Month Yield Spread (YIELD_SPREAD, 1994m1 – 2019m12)

The yield curve is one of the seminal indicators for predicting economic activity. The yield spread is included in many indices and forecasting models for US economic activity including Stock and Watson (1989), Dueker (1997), Kauppi and Saikkonen (2008), Ng (2012) and more. While spreads of varying treasury rates can be used, the author uses the series that is calculated as the 10-year Treasury constant maturity minus the 3-month Treasury constant maturity. The data is from the U.S. Treasury Department and the Federal Reserve Bank of St. Louis. The lag length used on the yield spread indicator is 6-months. The direction of the correlation and the results of the leading probit follow economic intuition in that an increase in the yield spread reduces the likelihood that a recession will occur while a decreasing, or negative, spread would increase the likelihood of a recession.

Ted Spread (TED_SPREAD, 1994m1 – 2019m12)

The Ted Spread is used as an indicator in the dynamic probit literature by Ng (2012). The series is calculated as the spread between the 3-month LIBOR based on US Dollars and the 3-month treasury bill. The data used is from the Federal Reserve Bank of St. Louis. It is originally calculated in daily frequencies but was extracted as monthly data using an average aggregation method. Unlike the yield spread, an increase in the Ted Spread is positively correlated with the binary recession variable and increases the likelihood of a recession. This makes intuitive sense as foreign interest rates that are substantially higher than domestic interest rates create foreign investment to appear more attractive. So, when the Ted Spread is largely positive this is harmful for the United States' economic activity (Nyberg, 2010).

Match Efficiency with U-6 (M_6, 1994m2-2018m12)

The match efficiency captures the relationship of three key labor market variables: hires, unemployment, and job vacancies[18]. The author argues that including the match efficiency over independent labor market variables creates a stronger representation of the dynamic labor market behavior[19]. Based on the findings from Chapter 2, it was important to test the match efficiency using each definition of unemployment in the leading probit model. Unsurprisingly, the measure with U-6 was the optimal choice. This aligns with findings that the percent change in workers who are part time for economic reasons is optimal in the coincident index.

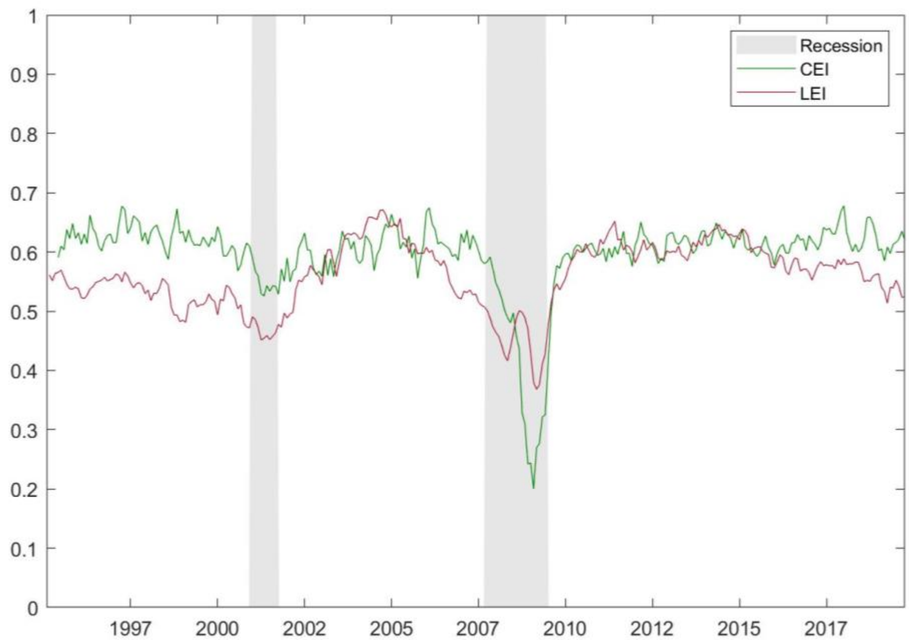
The lag length of 12 months on the match efficiency is the longest of the leading indicators. This result follows the findings from Crawley and Welch (2019) who use a Vector Error Correction model to show that while in the short run, an increase in the match efficiency creates an increase in employment, the long run effects of an increase in the match efficiency create a decrease in the employment rate. These findings also support the directional effect of the match efficiency. The negligible short run effects can be seen in the correlation between the match efficiency with no lag structure and the binary recession indicator; however, an increase in the 12-month lag of the match efficiency increases the likelihood of a recession.

[18] For methods on calculating the match efficiency, see Chapter 1.
[19] The lagged labor force participation indicator is tested in place of the match efficiency and yields a poorer model. See Appendix B Model 5 for justification.

3.5. Index Results

The index made up of coincident indicators (CEI) and the index composed of leading indicators (LEI) are presented together in Figure 3.3[20].

Figure 3.3. Coincident and Leading Economic Indices



There are strengths and issues with both indices. For the CEI, the strength is that the sharp decline for a recession is evident and easy to spot; however, when the economy is not in recession the index remains relatively flat. For the LEI, the index moves ahead of a recession. Although this paper does not intend to forecast, from ocular estimation this leading index turns too far in advance of an economic downturn and may not be as useful when predicting future trends (Mazziotta and Pareto, 2013).

[20] Both indices are smoothed to remove excess noise. For a smoothed vs. unsmoothed comparison, see Appendix C.

This paper proposes combining the two indices together to form a more effective index that combines current economic activity as well as leading activity. For the purposes of this paper, the method of combination is to equally weight all coincident and leading indicators used into a singular composite index. However, when looking at correlations across all variables, the 6-Month Corporate vs Treasury Spread indicator in the CEI is highly correlated with the Ted Spread used in the LEI. Therefore, only one of these indicators should be used in the final index to avoid redundancy (Salzman, 2003).

The index with the Corporate Spread (COMP_INDEX_CPS), and the index with the Ted Spread (COMP_INDEX_TED) were both tested using probit models with the binary recession indicator as the dependent variable, a similar method to how the individual indicators were selected.

Table 3.6. Probit Models for Composite Indices

Model	(1)	(2)
Independent Variable	COMP_INDEX_CPS	COMP_INDEX_TED
Parameter Estimate	-46.046***	-52.335***
	(7.8118)	(9.5411)
N	296	296
Log Likelihood	-22.319	-19.186
Pseudo R^2	0.7701	0.8024
AIC	48.639	42.372
BIC	56.020	49.753

*Note: Standard errors of parameter estimates are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$*

From the results presented in Table 3.6, it is evident that the index with the Ted Spread has the superior model fit. For the final results, figure 3.4 shows the selected composite index as well as the coincident and leading economic indices.

Figure 3.4. Final Indices

Looking at the composite index in Figure 3.4, the economy has been relatively stable since 2010. Currently both the composite and leading indices have a downward trajectory; but the slope is much flatter than the downward movement before the great recession.

3.6. Discussion

The construction of the composite index is successful because it clearly shows previous recessions and leads by a time period that is less extreme than the leading index itself. The index also supports that the economy has been stable over the past 8 years since the recovery. In terms of meeting the guidelines of Mitchell and Burns (1938), the index leads a negative cyclical change by at least three months, does not have erratic movements in the middle of the cycle, and moves in a clear direction.

Despite meeting these guidelines, the time period with available data is a major limitation for this index. There have only been two observable recessions and an historically long period of expansion, how it would perform during different business cycle conditions is yet to be assessed. The two recessions in this data are drastically different; therefore, it is hard to understand if future behavior of the index will exhibit past behavior. In addition, while the flat path does provide evidence of a stable economy, the lack of cyclical movement during times of expansion potentially make it less useful for policymakers.

Beyond the index itself, using the dynamic probit models for variable selection was a success of this paper. The approach confirmed that many of the key indicators in measuring economic activity, such as manufacturing and the yield spread, are still effective. It also provided insight on directional effects of the indicators in regard to the likelihood of recessions. An important result from the dynamic probit is that the matching efficiency can and should be used as a leading indicator. The match efficiency captures unemployment, vacancies, and hiring in the labor market; encompassing more labor market dynamics than the unemployment rate alone.

3.7. Conclusion

Overall, the paper provide insight into the economic activity before, during, and after the recession. Results from the composite index suggests that the economy has been stable since the recovery of the great recession; but there currently is a slight downward trend. A novel finding from the paper is that matching efficiency can be used as a leading indicator to capture labor market dynamics and should be used over other labor market indicators.

It is important to reiterate that this is a preliminary analysis of the composite index, and future research should include testing more sophisticated weighting mechanisms, such as principal component analysis, to improve accuracy. Another important task for future research will involve forecasting within the index. This may occur at the individual indicators as well as the entire index as a whole. Similarly, future work will also ensure that the index is updated in a timely manner and will adjust based on revisions in the secondary data used.

CHAPTER 4

CONCLUSIONS

The chapters in this thesis sought to answer four questions: (1) How do alternative measures of unemployment change the labor market matching efficiency? (2) Within a matching function framework, have labor market dynamics changed since the great recession? (3) Can the match efficiency be used as an effective indicator in a composite economic index? (4) Following the great recession, how does a composite index look now?

Chapter 2 finds that using data that include discouraged workers, workers marginally attached to the labor force, and/or those that are unemployed decrease the labor market match efficiency. This paper also finds that the matching efficiency calculated by using U-6[21] is most correlated with employment from 2008-2018, following the recession. These findings indicate that labor market dynamics have changed since the great recession; supported by the abnormalities that can be observed in the temporal comparison between the unemployment and vacancy rates in Figure 2.1 and the Beveridge curve in Figure 2.5.

Findings form Chapter 2 lead to the novel contribution from Chapter 3; the match efficiency can, and should, be used as a leading indicator. The lag length on the match efficiency is 12 months, and the longest for the indicators. Another important note is that the matching efficiency with U-6 outperforms the U-3, U-4, and U-5 match efficiencies in the index. Using the U-6 match efficiency provides insight on a variety of labor market conditions; including unemployment, underemployment, vacancies, and hiring. In addition, it reiterates the importance of analyzing underemployment, supporting the findings from Chapter 2.

[21] Total unemployed, plus all persons marginally attached to the labor force, plus total employed part time for economic reasons.

Overall, Chapter 3 confirms that many of the traditional indicators still maintain their importance when constructing a composite index. In terms of current behavior, after the recession the index has been relatively flat with a slight downward trend, but not as severe as it was leading up to the great recession. The index as a whole is more preliminary, and future work should include further exploration of more sophisticated weighting mechanisms for the indicators as well as forecasting of the index.

Ultimately, this thesis confirms that the matching efficiency is an important tool when analyzing labor market conditions and could provide insight to the health of the wider economy. By including an unemployment rate that captures workers who are discouraged, marginally attached to the labor force, and underemployed allows for greater insight of labor market dynamics beyond the traditional unemployment rate. The continued exploration of the U-6 match efficiency will be more important as time goes on and the economy enters a new cycle.

After the research for this thesis was completed but before the defense of the work, a global pandemic has disrupted the economy. Interest rates have dropped, productivity is slowing, and stock markets have plummeted. One area of the economy that has massively changed in a matter of weeks is the labor market. Unemployment claims are spiking, vacancies are disappearing, and hires have nearly halted. These changes are going to affect more people than those who are currently in the labor force, and the underlying frictions discussed in this thesis could have knock-on implications to the current shock. While neither the match efficiency nor the composite index could have predicted the pandemic, it will be interesting to observe how they behave during the recovery.

Ultimately, policymakers should take note of the importance of underemployment. The key takeaway from this thesis is that the matching efficiency using the U-6 definition of unemployment is an important indicator when discussing labor market health and economic health as a whole. Attention to this metric will be needed going forward. As the country recovers from the COVID-19 pandemic, there will likely be a large flow of workers from unemployed to underemployed while the markets adjust and restrictions on businesses are loosened. By only focusing on the number of unemployed workers, huge frictions may be missed during this transition. Underemployed workers creates mismatch in the supply and demand for labor, and the lingering frictions could have larger adverse effects going forward if they are ignored.

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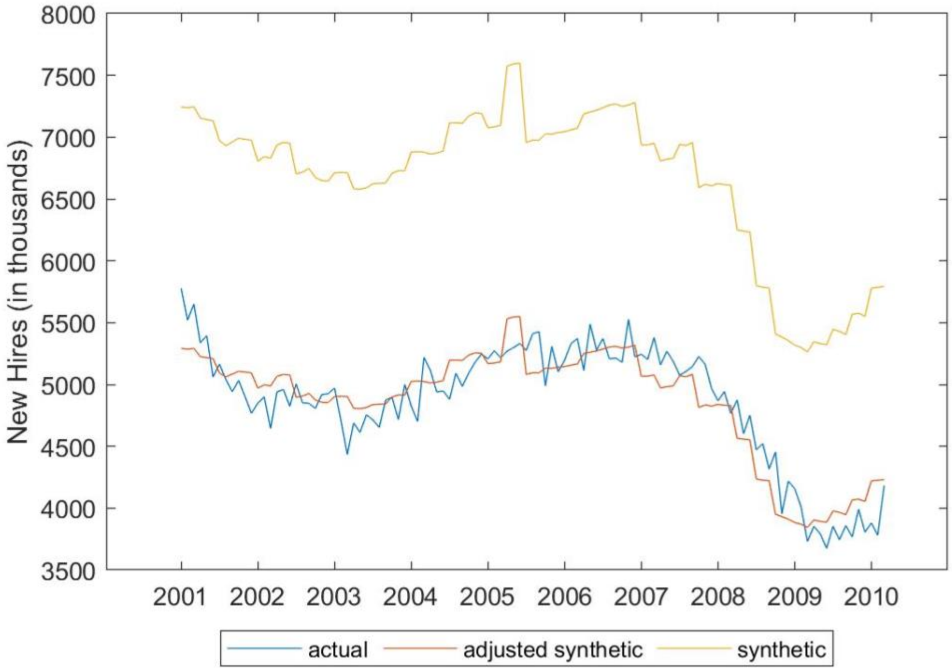
APPENDICES

A. New Hires Data

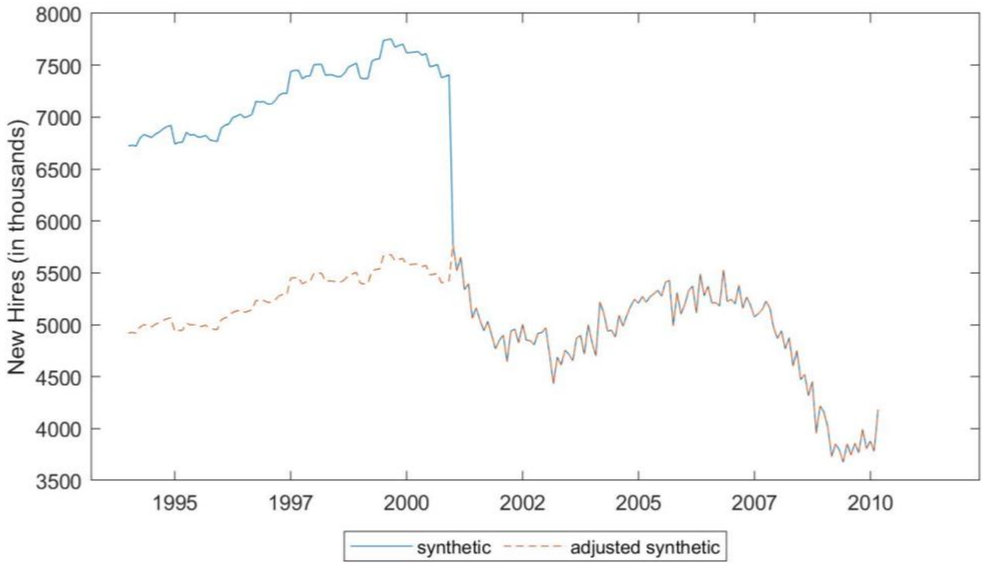
Hires data from 1994 through 2000 are modified from the synthetic JOLTS estimation from Davis et al. (2012) who use total hires as a percentage of employment to compute a hiring rate which spans from 1990 through 2010. This rate is then multiplied by employment to get an estimate of hires in levels. However, when comparing the estimated level of hires to the actual JOLTS data from 2001 to 2010, it is evident that this method produces an overestimate of true hires. To correct for this, we compute the ratios of actual JOLTS to synthetic JOLTS, which span from 0.65 to 0.82 with a standard deviation of 0.03. Then, we adjust the synthetic JOLTS from 1994 through 2000 by the average ratio of 0.73. Figure A.1 present the actual JOLTS hires from 2001 thru 2010, the synthetic hires from 2001 thru 2010, and our adjusted synthetic hires from 2001 thru 2010.

Figure A.1. Actual vs. Synthetic Hires



To further emphasize why an adjustment was needed, Figure A.2 presents the synthetic hires and the adjusted synthetic hires from 1994-2000. Both series are then combined with the actual JOLTS data in 2001.

Figure A.2. Synthetic and Adjusted Synthetic Hires



B. Model Tests

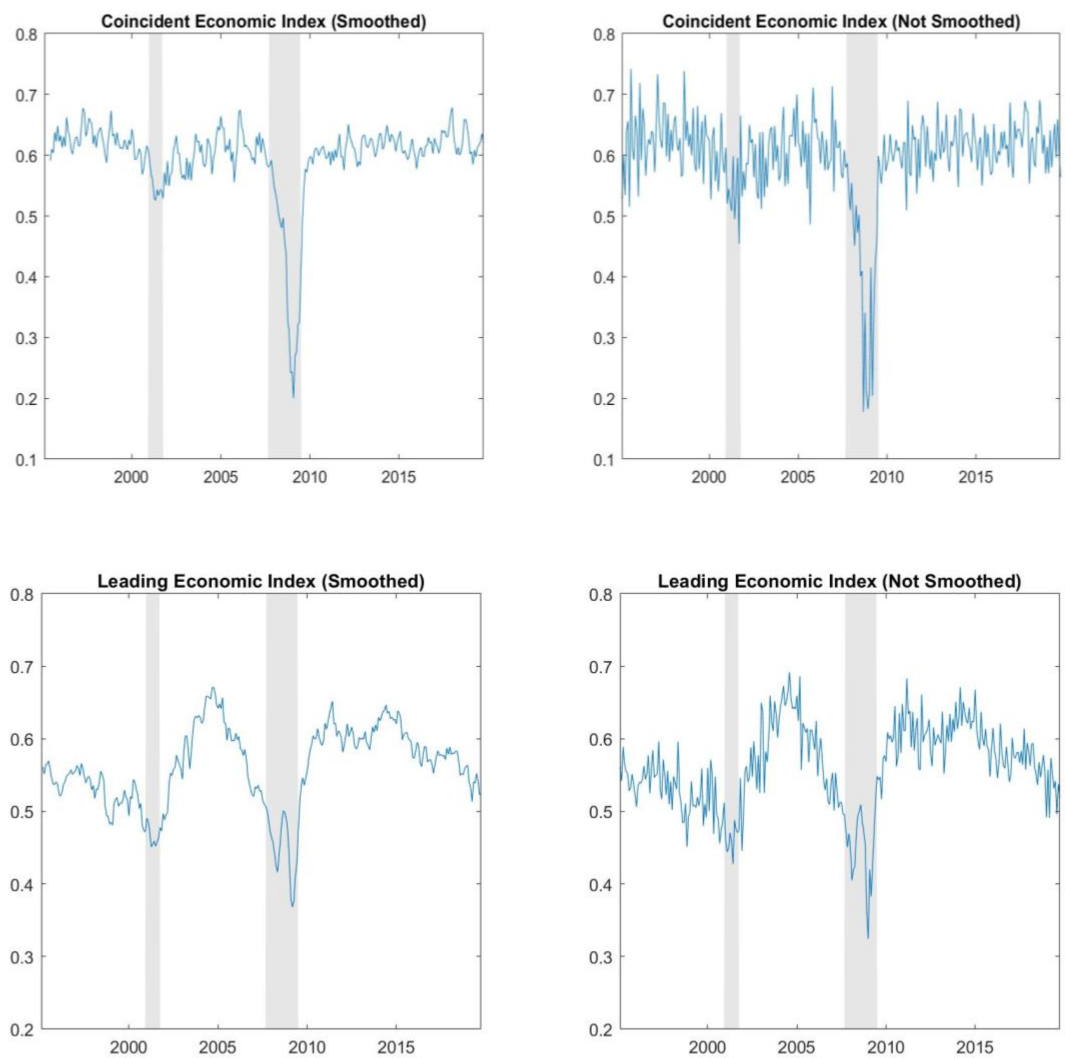
Table B.1. Dynamic Probit Model Results with Alternative Indicators

	(1)	(2)	(3)	(4)	(5)
Model Description	Model Used	Replace 6-month lag of MUO with 12-month lag of MUO	Replace Permits with House Price Index	Remove Retail Sales	Replace Match Efficiency with Labor Force Participation
Variables					
L3.INC_LTP	-2.315***	-1.440***	-2.404***	-2.031***	-3.634**
L6.MUO	-1.256*	--	-1.418**	-0.804**	-0.511**
L12.MUO	--	-0.247	--	--	--
L3.YTB_10	-4.512**	-2.461	-3.386**	-3.639**	-2.534
L3.SP_500	-0.269**	-0.095	-2.05***	-0.165**	-0.207***
PERMIT	-0.013***	-0.009***	--	-0.01***	-0.015***
L3.HOUSE_PRICE	--	--	-3.415***	--	--
L.RETAIL_SALES	-0.744	-0.210	-0.592**	--	-0.636*
L6.YIELD_SPREAD	-3.197***	-1.662***	-1.783***	-2.27***	-3.829***
L3.TED_SPREAD	3.685*	1.425	3.937***	2.163*	5.089***
L12.M_6	44.875***	33.960***	24.149**	42.89***	--
L12.LFP	--	--	--	--	6.356**
Pseudo R-Squared	0.889	0.839	0.811	0.874	0.869
Log Likelihood	-10.843	-15.723	-18.432	-12.32	-12.723
AIC	41.686	51.447	56.865	42.641	45.446
BIC	78.691	88.451	93.869	75.945	82.484

*Note: * indicates p < 0.10, ** indicates p < 0.05, *** indicates p < 0.01*

C. Smoothing Final Indices

Figure C.3. Coincident and Leading Economic Indices, Smoothed vs. Unsmoothed



BIOGRAPHY OF THE AUTHOR

Sarah Maeve Welch was born in North Conway, New Hampshire and was raised in Center Lovell, Maine. She graduated from Fryeburg Academy in Fryeburg, Maine in May 2014. In May 2018, she graduated summa cum laude from The University of Maine with a Bachelor of Science in Financial Economics and a minor in Mathematics. During her undergraduate career, she worked as a teaching assistant and a research assistant for the School of Economics. Sarah was involved in the Student Portfolio Investment Fund and was a member of the All Maine Women honor society. She has presented at *North American Regional Science* conferences in 2017, 2018, and 2019. Sarah published an academic paper in *Applied Economic Letters* in 2019. She is a candidate for the Master of Science degree in Economics from The University of Maine in May 2020.