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Abstract

Initial jobless claims provide a weekly snapshot of the labor market. While known for being volatile, when put into the appropriate context initial jobless claims provide valuable information on the state of the labor market. This paper introduces a *threshold of initial jobless claims* that serves as a basis of comparison for the weekly reading of initial jobless claims. Observed initial jobless claims above the threshold are associated with a rising unemployment rate, and vice-versa. The results of an out of sample forecasting experiment show that considering the deviation of initial jobless claims from the threshold of initial claims can improve forecasting accuracy of one month ahead unemployment rate forecasts by three times more than using a conventional rule of thumb for initial jobless claims as well as outperform several time series models. The improvements in forecasting accuracy are strongest during recessions. The results of this paper suggest that there could be benefits to producing nowcasting models of the unemployment rate that incorporate initial jobless claims. Finally, as initial jobless claims are a measure of separations and are shown to aid in forecasting the unemployment rate, it appears that separations do play some role in influencing the unemployment rate.

Keywords: Initial Jobless Claims, Unemployment, Nowcasting, Separations

JEL codes: E37, E24, C53

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I. Introduction

The unemployment rate is one of the most commonly cited economic statistics, has been used in the Federal Open Market Committee's forward guidance for future monetary policy actions, and has been shown to be the best real time indicator on the current state of the labor market (Fleischman and Roberts 2011). Given this preeminence, accurate forecasts of the unemployment rate are of key policy importance. However, the experience at the end of 2013, when the unemployment rate fell rapidly and largely unexpectedly from 7.2 percent in October to 6.7 percent in December, highlights the difficulty in forecasting the unemployment rate even over a short horizon.¹

In an effort to advance forecasting accuracy of the unemployment rate, this paper introduces a method for improving one month ahead forecasts of the unemployment rate using data on initial jobless claims. Initial jobless claims report the number of individuals who have filed for unemployment insurance benefits in the previous week. As unemployment insurance is designed for individuals who have involuntarily lost their job, initial jobless claims provide a near direct measure of layoffs (Valletta and Kuang 2011).² Recent research has shown that layoffs are important in understanding the cyclical variation of the unemployment rate, especially in the beginning stages of a recession (Elsby et al. 2009), which suggests that initial jobless claims should be beneficial in detecting early warnings of an economic contraction. Additionally, initial claims is released with less than a one week lag, giving researchers a near real time look at the labor market. Given these beneficial features, initial jobless claims has been

¹ As an example of the unexpected nature of this decline, Blue Chip Forecasters in their November 2013 publication anticipated an average unemployment rate of 7.2 percent in the fourth quarter of 2013 (Blue Chip 2013). The unemployment rate averaged 7.0 percent for the fourth quarter of 2013.

² Hobijn and Sahin (2011) discuss that initial jobless claims also contains information on unemployed individuals' expected job finding probability. The authors write that when a larger share of laid off workers apply for initial jobless claims it can be inferred that these workers believe their job finding probability to be lower, and vice-versa.

frequently used in the forecasting literature to improve forecasts of the unemployment rate as well as the change in non-farm payrolls.³

Relating initial jobless claims to the flows of workers through the labor market (hires, quits, layoffs ect.) allows for the construction of a counterfactual estimate of initial jobless claims that corresponds to a constant unemployment rate. The contribution of this paper is this counterfactual estimate of initial jobless claims which I refer to as the *threshold of initial jobless claims*. The threshold is intended to serve as a basis of comparison for the weekly initial jobless claims report, as observed initial jobless claims above the threshold correspond to an expected increase in the unemployment rate and vice-versa. The threshold is constructed so that it is specific to a given month, and is available at the beginning of a month so that it can be compared to initial jobless claims as they are released throughout the month to update forecasts of that month's unemployment rate, which is not released until the beginning of the *following* month.

The results of an out of sample forecasting exercise show that a simple model that only considers the deviation of observed initial jobless claims from the threshold of initial jobless claims improves upon a suite of alternative forecasting models. This *Deviation from Threshold* model reduces the root mean square forecasting error (RMSFE) of one month ahead forecasts of the unemployment rate by over 22 percent relative to a random walk model. This is more than three times larger than the improvement when using a standard rule of thumb relating initial jobless claims to the labor market (i.e. comparing observed initial jobless claims to 400K, see Kliesen et al. 2011), and a noticeable improvement over ARIMA and AR models. Incorporating the deviation of observed initial jobless claims from the threshold into a standard AR model is

³ Montgomery et al. (1998) and Gavin and Kliesen (2002) use initial jobless claims to improve unemployment rate forecasts. McConnell (1998) as well as Kliesen and Wheelock (2012) use initial jobless claims to help in forecasts of non-farm payrolls.

also shown to improve forecasting accuracy relative to the standard AR model. These improvements in forecasting accuracy are strongest during the Great Recession, consistent with the notion that layoffs are of particular importance to the cyclical variation in the unemployment rate.

The forecasting experiment also shows that there is a benefit to updating the forecast of the unemployment rate with each weekly release of initial jobless claims, as there is some improvement in forecasting accuracy during later weeks of the month relative to earlier weeks. The improvement in current period forecasting accuracy as additional information is made available is a common feature of nowcasting models (Banbura et. al 2010). As the presented model uses regular, weekly updates of initial jobless claims to in-essence nowcast the monthly unemployment rate the results of this paper can contribute to the growing literature on nowcasting models that has largely ignored the unemployment rate. The nowcasting literature has primarily focused on variables released less frequently, such as quarterly GDP, but the presented results suggest there is a benefit to updating forecasts of the unemployment rate using the weekly initial jobless claims release.

The results of the forecasting experiment also weigh in on the recent debate on the relative importance of hires versus separations in influencing changes in the unemployment rate. Shimer (2005, 2012) and Hall (2005, 2006) argue that variation in the hiring margin is responsible for fluctuations in the unemployment rate, while Fujita and Ramey (2009) find that both the hiring and separation margins influence unemployment. Elsby et al. (2009) find that both margins matter when considering the cyclical variation in the unemployment rate, and Barnichon and Nekarda (2013) show that both margins are useful in forecasting unemployment. As initial jobless claims capture a segment of separations, and are shown to improve forecasts of

the unemployment rate, it appears that variation in separations plays at least some role in influencing changes in the unemployment rate. The improvement to forecasting accuracy is shown to be largest during the Great Recession, suggesting that separations are of particular importance to the cyclical changes in the unemployment rate, consistent with the work of Elsby et al. (2009).

The remainder of this paper proceeds as follows. Section II presents the methodology for estimating the threshold of initial jobless claims. Section III presents and discusses the results of a forecasting experiment that compares forecasts using the threshold of initial jobless claims to a suite of alternative forecasting models. Section IV discusses the implications of the results of the forecasting experiment with relation to the recent literature, and section V concludes.

II. Methodology

This section introduces initial jobless claims and then shows how they can be related to the different flows of workers through the labor market. Working in this framework, I generate a counterfactual estimate of initial jobless claims, referred to as the *threshold of initial jobless claims*, that corresponds to a constant unemployment rate, so that observed initial claims that are above the threshold are associated with a rising unemployment rate and vice-versa.

Initial jobless claims in period t (IC_t) is the number of laid-off individuals (L_t), times the fraction of those individuals filing a claim for unemployment benefits, i.e. the take-up rate of initial jobless claims (α_t)

$$IC_t = \alpha_t L_t \tag{1}$$

The change in employment in period t (ΔE_t) is the difference between hires (H_t) and separations, with separations being decomposed into quits (Q_t), layoffs (L_t), and other separations (O_t). Thus, changes in employment appear as:

$$\Delta E_t = H_t - Q_t - L_t - O_t \quad (2)$$

Solving for L_t in equation 2 and substituting the result into equation 1 yields the following expression for initial claims:

$$IC_t = \alpha_t(H_t - Q_t - O_t - \Delta E_t) \quad (3)$$

Equation 3 relates initial claims to the multiple margins of the labor market. Considering initial jobless claims in this manner, allows for creating a counterfactual estimate of initial claims given chosen values of the right hand side variables. Letting the take-up rate of initial claims (α_t), hires (H_t), quits (Q_t), and other separations (O_t) be observed as data, equation 3 then presents initial claims (IC_t) as a function of the change in employment (ΔE_t). Picking ΔE_t as the change in employment associated with a constant unemployment rate returns the level of initial claims that corresponds to an unchanging unemployment rate.⁴ This counterfactual estimate of initial claims corresponding to a constant unemployment rate will be the *threshold of initial jobless claims* that when used as a basis of comparison for observed initial claims, gives an indication on the upcoming change in the unemployment rate.

The change in employment associated with a constant unemployment rate is referred to as the *breakeven change in employment*, and is denoted ΔE_t^* . To derive ΔE_t^* , start by considering the change in the unemployment rate (ΔUR_t) between periods $t - 1$ and t

⁴ Pandl (2011) also uses this framework and sets $\Delta E_t = 0$ to arrive at a counterfactual estimate of initial jobless claims that can identify employment growth.

$$\Delta UR_t = UR_t - UR_{t-1} = \frac{U_t}{L_t} - \frac{U_{t-1}}{L_{t-1}} = \frac{L_t - E_t}{L_t} - \frac{L_{t-1} - E_{t-1}}{L_{t-1}} = \frac{-E_t}{L_t} + \frac{E_{t-1}}{L_{t-1}} \quad (4)$$

Where U is the number of unemployed individuals, E is the number of employed individuals, and L is the size of the labor force as reported in the Current Population Survey (CPS). Pick E_t^* such that $\Delta UR_t = 0$, then equation 4 can be rewritten as⁵

$$0 = \frac{-E_t^*}{L_t} + \frac{E_{t-1}}{L_{t-1}}$$

Subtracting E_{t-1} from both sides, and solving for $E_t^* - E_{t-1}$ yields

$$\Delta E_t^* = E_{t-1} \frac{L_t}{L_{t-1}} - E_{t-1} = \frac{E_{t-1}}{L_{t-1}} (L_t - L_{t-1})$$

Rewriting E_{t-1} as $(L_{t-1} - U_{t-1})$ and observing $\frac{U_{t-1}}{L_{t-1}} = UR_{t-1}$, where UR_{t-1} is the unemployment rate in period $t - 1$ returns the following expression for the breakeven change in employment

$$\Delta E_t^* = (1 - UR_{t-1})(\Delta L_t) \quad (5)$$

Thus, the change in employment required for the unemployment rate to remain constant, is simply the share of the labor force that is employed at the start of the period $(1 - UR_{t-1})$ times the change in the size of the labor force during the period (ΔL_t) .⁶

II.B Threshold of Initial Claims

⁵ Picking E_t^* in this manner assumes the labor force remains the same size in the counterfactual exercise as in reality. In essence, this assumes the appropriate number of workers move between the states of employment and unemployment to generate a constant unemployment rate. While this might seem like a restrictive assumption, Shimer (2012) shows that reasonable labor market dynamics can be obtained by only considering transitions between the states of employed and unemployed.

⁶ The breakeven change in employment (ΔE_t^*) is presented in the Appendix.

With an estimate of the breakeven change in employment (ΔE_t^*) the threshold of initial jobless claims can be estimated. This subsection discusses the final details of the estimation of the threshold of initial jobless claims. The threshold is then presented, its experience over the most recent business cycle is discussed and deviations of observed initial jobless claims from the threshold are then empirically examined in conjunction with changes in the unemployment rate.

The threshold of initial jobless claims, denoted IC_t^* , appears as

$$IC_t^* = \alpha_t(H_t - Q_t - O_t - \Delta E_t^*) \quad (6)$$

Data on total private hires (H_t), quits (Q_t), other separations (O_t) and layoffs (L_t) are available from the Job Openings and Labor Turnover Survey (JOLTS) and the take-up rate of initial claims (α_t) is calculated by dividing the monthly average of initial claims by layoffs. The breakeven change in employment (ΔE_t^*) is estimated using the unemployment rate and size of the labor force from the CPS as shown in equation 5. To smooth through the volatility in these series I exponentially smooth each of the series that enter into equation 6.⁷

The JOLTS release provides very detailed information on the flows of workers through the different states of the labor market. However, this information comes at the cost of timeliness. JOLTS data is released with a lag of approximately two months, for instance JOLTS data for November 2013 was not released until January 2014. This poses a problem if the threshold of initial jobless claims presented in equation 6 is to be estimated in real time and used to forecast the unemployment rate.⁸ Again consider January 2014. The forecaster is interested in what the unemployment rate is going to be for the month of January, which is released in

⁷Specifically, I exponentially smooth the data so that the smoothing parameter is chosen to minimize the in-sample sum of squared forecast errors. Additionally, note that the presented results are robust to the method of smoothing, similar results are obtained if three month moving averages are used to smooth the series rather than exponential smoothing.

⁸Also observe that to estimate ΔE_t^* the size of the labor force in period t is also needed, which is not available to the forecaster before the unemployment rate for month t is available.

February. Data on initial jobless claims are released throughout January, containing information about the labor market in January. However the data on hires, quits, layoffs and other separations from JOLTS that are available in January are in reference to hires, quits ect. in November 2013. Thus, as equation 6 stands the most up to date threshold of initial claims that could be estimated is for November 2013.

To facilitate calculating the threshold in real-time, data from the JOLTS survey (hires, quits, layoffs and other separations) enter into equations 6 as two month lags. Again, consider January 2014. JOLTS data on the labor market in November are effectively pushed forward two months, and assumed to be January's estimates so that a threshold of jobless claims for January can be estimated *in* January. For consistency the remaining variables that are used to calculate the threshold also enter equation 7 in two month lags. With these adjustments the threshold of initial jobless claims appears as

$$IC_t^* = \alpha_{t-2}(H_{t-2} - Q_{t-2} - O_{t-2} - \Delta E_{t-2}^*) \quad (7)$$

Again, estimating the threshold of initial jobless claims in this manner allows for the threshold to be calculated in real time, and be compared to observed initial jobless claims (IC_t) as they are being released so that the differences between the two can be used in producing a real time forecast of the unemployment rate.

The threshold of initial claims is presented in Figure 1 alongside the four week moving average of initial jobless claims from the fourth week of each month. Recall the threshold was constructed to serve as a basis of comparison for observed initial claims, such that observed claims above the threshold were associated with a rising unemployment rate and vice-versa. Comparing observed initial claims to the threshold in Figure 1, the most recent business cycle is

readily apparent. Observed claims moved above the threshold at the onset of the recession, and concurrently the unemployment rate increased. Following the recession, initial claims moved below the threshold and have stayed below in nearly every month, and over this period the unemployment rate has steadily declined. Thus, over the most recent business cycle comparisons of observed initial claims to the threshold appear to be accurately capturing changes in the unemployment rate.

The figure also shows that the threshold of initial jobless claims moves counter cyclically. The counter cyclical nature of the threshold indicates that in a weaker labor market an unchanging unemployment rate can occur despite an elevated level of initial claims. Further, an elevated level of initial claims can indicate improvement in the labor market as long as observed initial claims are below the threshold. For example, between September of 2010 and October 2011 observed initial claims were above 400 thousand but below the threshold in each month. Thus, over this period, the common benchmark of 400 thousands suggests that labor market conditions were worsening (see Kliesen et al. 2011), while the threshold indicated improvement. In fact, during this period the unemployment rate decreased by nearly 0.7 percentage points. This shows that despite being *elevated* by the common benchmark of 400 thousand, initial claims were correctly showing improvements in the labor market when compared to the threshold.

To gauge if deviations of observed initial jobless claims from the threshold of initial claims are associated with changes in the unemployment rate the following regression model is considered

$$\Delta UR_t = \beta_0(IC_t - IC_t^*) + \varepsilon_t \quad (8)$$

In equation 8, ΔUR_t is the change in the unemployment rate in month t , IC_t is the four week moving average of initial jobless claims from the fourth week of month t and IC_t^* is the threshold of initial jobless claims from equation 7.⁹ If the coefficient β_0 is statistically greater than zero, then observed initial claims above the threshold are associated with a rising unemployment rate, and observed initial claims below the threshold are associated with a declining unemployment rate. Equation 8 is estimated using ordinary least squares (OLS) on the sample from February 2001 to December 2013.¹⁰ The results of the estimation are presented in Table 1.

The results presented in the first column of Table 1 provide statistical support that deviations of observed claims from the threshold are associated with changes in the unemployment rate over the sample period. The coefficient on the variable *Deviation from Threshold* indicates that when the observed four week move average of initial jobless claims is above the threshold there is upward pressure on the unemployment rate, and when observed claims is below the threshold there is downward pressure. Columns 2 and 3 of Table 1 show that the statistical significance of a positive association between deviations of observed initial claims from the threshold and changes in the unemployment rate is robust to the inclusion of lagged changes in the unemployment rate entering into equation 8.¹¹

The regression results indicate the larger the size of the deviation of initial jobless claims from the threshold, the greater the pressure on the unemployment rate. Figure 2 provides a graphical representation of this linear relationship.¹² Intuitively, if observed initial claims is equal to the threshold at the start of a period and layoffs decrease during the period, initial claims

⁹The four week of the month was selected as it contains information on the entire month. The presented results are robust to selecting initial jobless claims from the fourth week of the month to be used in the regression.

¹⁰ Another caveat of the JOLTS data is that it is only available starting in December 2000

¹¹ The use of 1 lag in column 2 and 4 lags in column 3 were chosen by the BIC and AIC, respectively.

¹² Note that this scatter plot with the intercept set to zero is a visual representation of equation 8.

will move below the threshold, holding all else constant. The decrease in layoffs reduces the flow into unemployment and thus when observed initial claims move below the threshold it can be expected that the unemployment rate will decrease. When the decrease in layoffs is larger, the deviation from the threshold will be larger as will the reduced flow into unemployment, resulting in greater downward pressure on the unemployment rate.

II.C Using the Threshold of Initial Claims

This subsection reviews how forecasters can use the threshold of initial claims to obtain an updated forecast on the unemployment rate following the weekly releases of initial jobless claims.

In the first week of month t the Employment Report for month $t - 1$ is released, which contains the CPS estimates for the unemployment rate and size of the labor force in month $t - 1$. In the second week of month t JOLTS data on hires, quits, layoffs and other separations is released. Recall that the JOLTS data released are in reference to month $t - 2$; however, to facilitate having the threshold of initial jobless claims for month t available *in* month t , I effectively *push* the JOLTS data forward two months and assume it is representative of the labor market in month t . After pushing the JOLTS data forward two months the threshold of initial jobless claims for month t , denoted IC_t^* can be calculated using equation 7.¹³

At this point initial claims has typically been released once for month t .¹⁴ The forecaster can then compare the threshold of initial jobless claims to the most recently observed four week moving average of initial jobless claims to get an indication on the upcoming change in the unemployment rate. If the observed four week moving average of initial jobless claims is above

¹³ Again to use equation 7 to calculate the threshold of initial claims, I am assuming the data on hires, quits, other separations and the take-up rate from month $t - 2$ are representative of the labor market for month t .

¹⁴ Note that initial jobless claims are released on a Thursday but are in reference to the week that ended the prior Saturday. So it is possible that initial claims are released in month t but are in reference to month $t - 1$. Throughout the paper I am concerned with the month in which initial claims are referencing.

the threshold then the forecaster can predict that the unemployment rate will increase, and vice-versa. To get an estimate of the size of the change in the unemployment rate, the coefficient β_0 from the estimation of equation 8 is used as follows

$$\widehat{\Delta UR}_t = \beta_0(IC_t - IC_t^*) \quad (9)$$

This allows the forecaster to have a forecast of the unemployment rate for month t that incorporates information on the labor market in month t . The following week when the second report of initial jobless claims is released for month t the forecaster can again compare observed initial jobless claims to the threshold of initial jobless claims to produce an updated forecast of the unemployment rate. This process continues with each weekly report of initial jobless claims until the unemployment rate for month t is released at the start of month $t + 1$.¹⁵

III. Forecasting Experiment

The results presented thus far have been for in sample estimation of the threshold. However, the success of the threshold will be judged based on its ability in real time to access labor market conditions by making comparisons to observed initial jobless claims as they are being released. This section aims to address this issue by conducting an out of sample forecasting experiment and comparing the results using the threshold of initial claims to a suite of alternative forecasting models.

The forecasting experiment begins in forecasting the unemployment rate for January 2004. The experiment is out of sample in that to generate a forecast of the unemployment rate in month t , I only use information that would have been available to the forecaster before the release of month t 's unemployment rate. After generating an out of sample forecast for the

¹⁵ Note the process described above would be virtually identical if lags of the change in the unemployment rate were used in the regression equation as in columns 2 and 3 of Table 1.

unemployment rate in January 2004, the experiment then moves on to forecasting the unemployment rate for February 2004 in an out of sample manner. This process continues on until forecasting the unemployment rate in January 2014.

Out of sample forecasts are generated by comparing the observed four week moving average of initial jobless claims from each week of the month to the threshold of initial jobless claims as in equation 9. For instance, the four week moving average of initial jobless claims from the first week of a month is compared to the threshold of initial jobless claims for that month to produce a forecast of the unemployment rate for that month. This model is referred to as *Week 1 Deviation from Threshold*. Then the four week moving average of initial jobless claims from the second week of the month is compared to that month's threshold to produce an unemployment rate forecast, and is referred to as the *Week 2 Deviation from Threshold*. This process continues for the third and fourth week of each month. As some months have five weeks, I also consider the deviation of initial jobless claims from the threshold in the “final” week of each month, which is same as the deviation in the fourth week for months with only four weeks and the deviation in the fifth week for those months with five weeks. Updating the forecast of the unemployment rate in each week of the month, allows for accessing the degree to which forecasting accuracy varies over the month.

Forecasting ability is accessed based on a model M 's root mean square forecast error (RMSFE), which is calculated as

$$RMSFE_M = \sqrt{\frac{1}{P} \sum (\widehat{UR}_{M,t} - UR_t)^2} \quad (10)$$

where $\widehat{UR}_{M,t}$ is the forecast of the unemployment rate from model M in period t , and there are P one-step ahead forecasts of UR_t from model M . The RMSFE for each of the models that utilize the deviation of observed initial jobless claims from the threshold are presented in Table 2.

The RMSFE from the *Deviation from Threshold* models shows that the forecast accuracy improves as the month progresses, indicating that there is a benefit of updating the unemployment rate forecast at each release of the initial jobless claims during the month. This improvement in forecasting accuracy as more recent data are release is a common feature of nowcasting models (Banbura et al. 2010). Table 2 also shows the RMSFE of a random walk model of the unemployment rate. A random walk model forecasts an unemployment rate in month t that is equal to the observed unemployment rate in month $t - 1$, and can be considered a *naive* forecast. The third column of Table 2 shows the RMSFE errors from the *Deviation from Threshold* models relative to the RMSFE of the random walk model. Ratios below 1 indicate that considering deviations from the threshold improve upon unemployment rate forecasts relative to a random walk and vice versa. The relative RMSFE shows that the *Deviation from Threshold* models noticeably improve upon a naive forecast by over 22 percent. Thus, relative to a naive forecast, there is a benefit to comparing initial jobless claims to the presented threshold of initial jobless claims in real time to generate unemployment rate forecasts.

The deviation of observed initial claims from the threshold can also be incorporated into models that look at past values of the unemployment rate. Table 3 presents forecasting results for an AR(1) model and an AR(4) model of changes in the unemployment rate, as well as the AR models when deviations from the threshold are incorporated. Comparing the standard AR models to the AR models including the deviations from the threshold can access if incorporating the deviations from the threshold improve forecasting accuracy. The results show that there is a

noticeable reduction in RMSFE of the AR models when including deviations from the threshold. For the AR(1) the improvement relative to a random walk goes from 4 percent when using a standard AR(1), to over 20 percent when deviations from the threshold are included. In the case of the AR(4) the improvement relative to the random walk goes from just over 12 percent to between 21 and 24 percent. Thus, it appears deviations from the threshold are capturing relevant forecasting information missed in the AR models.

III.B Alternative Models

This section considers alternative models that can be used to forecast the unemployment rate, and compares their results in the forecasting experiment to the results presented above that use the threshold of initial jobless claims.

As a first alternative, I consider the commonly referenced 400K threshold of initial jobless claims (Kliesen et al. 2011). The 400K threshold posits that observed initial claims below 400K signal improving labor market conditions, and vice-versa. I consider using 400K claims in the same manner as in using the threshold of initial jobless claims. To forecast the unemployment rate in month t the following regression is estimated through month $t - 1$ following release of the unemployment rate for month $t - 1$

$$\Delta UR_t = \beta_0(IC_t - 400) + \varepsilon_t \quad (11)$$

where IC_t is the four week moving average of initial jobless claims from the fourth week of month $t - 1$. To generate the forecast of the unemployment rate for month t , equation 11 is estimated using OLS with data from February 2000 to month $t - 1$.¹⁶ Then using the coefficient

¹⁶ February 2000 is picked to be the starting date for the data used in the estimation of equation 11 to be consistent with the estimation of equation 8. However, as data on initial jobless claims and the unemployment rate are available prior to February 2000, a longer sample could be used to estimate equation 11. Note that the presented results are robust to estimating equation 11 over a longer period.

β_0 estimates of the unemployment rate in month t can be used as initial jobless claims are released throughout the month by comparing them to 400K, as follows

$$\widehat{\Delta UR}_t = \beta_0(IC_t - 400) \quad (12)$$

Here IC_t is the four week moving average of initial jobless claims released in month t , and again I update the forecast of the unemployment rate in month t with each weekly release of the initial jobless claims.

Table 4 shows the RMSFE of the models that use the *400K Deviation*, as well as the relative RMSFE when comparing to a random walk forecast. Similar to the results presented earlier, the forecasting accuracy of *400K Deviation* models improves as the month progresses, and improves upon the forecast generated by a random walk model. However, the improvement of the model relative to a random walk is not as large as the benefit that comes from comparing initial jobless claims to the threshold of initial jobless claims. At its best comparing initial jobless claims to the 400K threshold can reduce the RMSFE by just more than 7 percent relative to a random walk model, while comparisons to the threshold of initial jobless claims reduce the RMSFE by over 22 percent, more than three times the improvement seen with the 400K threshold.

As a second alternative to the forecasting model that uses the threshold of initial jobless claims I consider a time series model of the unemployment rate. Montgomery et al. (1998) show that ARIMA models can be used to accurately forecast the unemployment rate, and I fit an ARIMA(4,0,4) model on the monthly unemployment rate.¹⁷ To forecast the unemployment rate in month t the ARIMA model is estimated using data from January 1948 to month $t - 1$, the assumed last available reading of the unemployment rate, and then the parameter estimates are

¹⁷The parameters for the ARIMA model were selected by Bayes Information Criterion.

then used to generate the one step ahead forecast. I allow the ARIMA model to be estimated over a longer time horizon as a forecaster using this model to forecast the unemployment rate would have a longer estimation period than the one I use to fit the model that incorporates the threshold of initial jobless claims, which begins in February 2001. The results presented in Table 3 show that the ARIMA model improves upon a random walk, and *400K Deviation* models, but does not outperform the *Deviation from Threshold* models. The ARIMA model improves upon a random walk forecast by more than 14 percent, but this is smaller than the over 22 percent improvement that is seen by incorporating the threshold of initial jobless claims.

A downside of using a time series model such as the ARIMA or AR models is that they only incorporate information from prior months to generate a forecast for the current month. Thus, if there is a shock that occurs to the labor market in month t the ARIMA and AR models will be unable to incorporate that shock into the forecast of month t . Using initial jobless claims as a forecasting tool allows the forecaster to incorporate these shocks into their forecast, and comparing initial jobless claims to the threshold appears to provide an appropriate context with which to observe these shocks and improve forecasts of the unemployment rate.

The largest of these aggregate shocks occur around economic recessions. Thus, comparisons to the threshold could prove especially beneficial at these times. Table 5 compares the RMSFE of the *Deviation from Threshold* models as well as the alternative models during the 2008-09 recession (“the Great Recession”), that spanned from January 2008 to June 2009. The table shows that the models that compared initial jobless claims to the threshold of initial jobless claims (the *Deviation from Threshold* models) perform far better at forecasting the rise in the unemployment rate over this period relative to the other models. The models that only consider the deviation of observed initial jobless claims from the threshold improve upon the RMSFE of a

random walk model by between 49 and 52 percent over this period. Models that incorporated lagged values of the change in the unemployment rate provided further improvements in forecasting accuracy, ranging from 50-56 percent improvement using an AR(1) with deviations from the threshold and 54-62 percent for an AR(4) with deviations from the threshold. These are far larger improvement than by using models that compare initial jobless claims to the 400K threshold (21-23 percent), forecasting with an ARIMA model (33 percent) or the standard AR models that do not incorporate deviations from the threshold (9 percent and 34 percent improvement relative to the random walk for the AR(1) and AR(4), respectively). Thus, it appears comparing observed initial jobless claims to the threshold of initial claims is particularly helpful in guiding unemployment rate forecasts during economic contractions.

IV. Discussion

This section considers the results of the forecasting experiment and places them in the context of the recent literature. In particular, with reference to the recent discussion of nowcasting models and the renewed interest in considering the relative importance of hires versus separations in influencing changes in the unemployment rate.

Recent papers have considered using more frequently available data to generate real time forecasts of less frequently reported, but perhaps more economically significant variables. This *nowcasting* literature has largely focused on forecasts of current quarter GDP and inflation.¹⁸ Despite the attention paid to the unemployment rate, little work has been done on nowcasting the unemployment rate. This potentially stems from its somewhat frequent and timely, monthly

¹⁸For nowcasting models of GDP see the seminal paper by Giannone, Reichlin and Small (2008) as well as Lahiri and Monokroussos (2013). For nowcasting models of US inflation see Modugno (2013) or Knotek II and Zaman (2013).

updates. However, the weekly reporting of initial jobless claims allows for shocks that occur during the month that is being forecasted to be captured and incorporated into the forecast.

The results shown in this paper can contribute to this nowcasting literature. The presented forecasting experiment demonstrates that incorporating initial jobless claims in conjunction with the threshold of initial of initial jobless claims can noticeably improve forecasts of the unemployment rate one month ahead. Further, as forecasts for future months (past one month ahead) are dependent upon one month ahead forecasts in iterative forecasting models, improving the forecasting accuracy of one month ahead forecasts could lead to improved forecasts several months into the future.¹⁹

Additionally, the results of this paper can also contribute to the recent discussion on the importance of hires versus separations in explaining movements in the unemployment rate. Shimer (2005) and Hall (2005, 2006) find that variation in the hiring margin largely explains the movement in the unemployment rate. Shimer (2012) extends his earlier findings, and concludes that since 1948 the hiring margin (or job finding probability) accounts for 75 percent of the fluctuations in the unemployment rate, but that over the past twenty years the hiring margin has accounted for nearly all of the fluctuations.

Conversely, Fujita and Ramey (2009) find that both the hiring and separation margins matter for understanding movements in the unemployment rate. Elsby et al. (2009) find similar results that both margins matter in considering the cyclical variation in the unemployment rate. In particular, Elsby et al. (2009) note that the separations margin is especially important at the onset of an economic contraction. Additionally, Barnichon and Nekarda (2012) find that both the hiring and separation margins are helpful in forecasting the unemployment rate.

¹⁹For more on how comparing initial jobless claims to the threshold of initial jobless can improve forecasts of the unemployment rate up to 6 months into the forecast horizon see Braxton (2014).

In this paper, initial jobless claims were shown to aid in the forecast of the unemployment rate when compared to a threshold of initial jobless claims. As initial jobless claims are a measure of separations, this suggests that the separations margin does play some role in explaining the movements of the unemployment rate. The comparisons of initial jobless claims to the threshold were shown to be particularly useful when forecasting the unemployment rate during the Great Recession. Thus, concurrent with Elsby et al. (2009) there is evidence that the separations margin is especially important during economic downturns.

V. Conclusion

Initial jobless claims provide an up to date, weekly snapshot of the labor market. When put into the appropriate context initial jobless claims can provide labor market followers with timely and accurate information on the state of the labor market. This paper introduced a new context, *the threshold of initial jobless claims*, in which to analyze initial jobless claims. The threshold is constructed so that observed initial claims above the threshold are indicative of upward pressure on the unemployment rate and vice-versa.

The results of an out of sample forecasting experiment showed that comparing the observed four week moving average of initial jobless claims to the threshold can improve forecasts of the upcoming release of the unemployment rate. The improved forecasting accuracy is strongest when forecasting during recessions. These results suggest that there could be a benefit to policy makers and forecasters of considering nowcasting models of the unemployment rate, which build upon the weekly release of initial jobless claims.

Finally, the presented results contribute to the recent discussion on the relative importance of hires versus separations in explaining movements in the unemployment rate. As

initial jobless claims are a measure of separations, and were shown to improve unemployment rate forecasts, especially around recessions, it appears that separations play a role in the changes in the unemployment rate.

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Table 1: Regression Results

	(1)	(2)	(3)
	Change in Unemployment	Change in Unemployment	Change in Unemployment
Deviation from Threshold	0.00144*** (10.48)	0.00176*** (9.15)	0.00245*** (8.00)
L1.Change in Unemp. Rate		-0.161* (-1.93)	-0.215** (-2.55)
L2.Change in Unemp. Rate			-0.0870 (-1.06)
L3.Change in Unemp. Rate			-0.131* (-1.71)
L4.Change in Unemp. Rate			-0.205*** (-2.63)
Constant		-0.0205* (-1.90)	-0.0260** (-2.43)
Observations	155	155	155
R-squared	0.416	0.435	0.471
Adjusted R-squared	0.412	0.428	0.453

Note: This table presents estimates on the influence of deviations of observed initial jobless claims from the threshold of initial jobless claims in month t on changes in the unemployment rate for month t . Data from February 2001 to December 2013 is used in the estimation. Lag lengths in columns 2 and 3 were chosen by the BIC and AIC, respectively. T-statistics are reported in parenthesis. * $p < 0.1$ ** $p < 0.05$ *** $p < 0.01$.

Table 2: Out of Sample Forecasting Results using Threshold of Initial Jobless Claims

Model:	RMSFE	Relative RMSFE
Week 1 Deviation from Threshold	0.1368	0.7783
Week 2 Deviation from Threshold	0.1358	0.7725
Week 3 Deviation from Threshold	0.1348	0.7670
Week 4 Deviation from Threshold	0.1346	0.7661
Final Week Deviation from Threshold	0.1337	0.7610
Random Walk Model	0.1757	1.0000

Note: Forecasts were generated between January 2004 and January 2014. Forecasts for the deviation model were generated using the method described in the text and equation 9. The random walk model assumes that the unemployment rate in month t will be same as in month $t - 1$. The RMSFE for each forecasting model were calculated using equation 10. The relative RMSFE for a model is the RMSFE of that model relative to the RMSFE of the random walk model.

Table 3: Out of Sample Forecasting Results using Threshold of Initial Jobless Claims and Lagged Changes in the Unemployment Rate

Model:	RMSFE	Relative RMSFE
AR(1)	0.1688	0.9605
AR(1) w/ Week 1 Deviation from Threshold	0.1407	0.8006
AR(1) w/ Week 2 Deviation from Threshold	0.1388	0.7899
AR(1) w/ Week 3 Deviation from Threshold	0.1373	0.7812
AR(1) w/ Week 4 Deviation from Threshold	0.1371	0.7802
AR(1) w/ Final Week Deviation from Threshold	0.1359	0.7731
AR(4)	0.1542	0.8776
AR(4) w/ Week 1 Deviation from Threshold	0.1386	0.7885
AR(4) w/ Week 2 Deviation from Threshold	0.1360	0.7738
AR(4) w/ Week 3 Deviation from Threshold	0.1341	0.7634
AR(4) w/ Week 4 Deviation from Threshold	0.1343	0.7645
AR(4) w/ Final Week Deviation from Threshold	0.1333	0.7587

Note: Forecasts were generated between January 2004 and January 2014. The AR models are estimated on the monthly change in the unemployment rate. The RMSFE for each forecasting model were calculated using equation 10. The relative RMSFE for a model is the RMSFE of that model relative to the RMSFE of the random walk model.

Table 4: Out of Sample Forecasting Results using Alternative Models

Model:	RMSFE	Relative RMSFE
Week 1 400K Deviation	0.1656	0.9425
Week 2 400K Deviation	0.1653	0.9405
Week 3 400K Deviation	0.1645	0.9361
Week 4 400K Deviation	0.1642	0.9343
Final Week 400K Deviation	0.1633	0.9294
ARIMA(4,0,4)	0.1506	0.8572

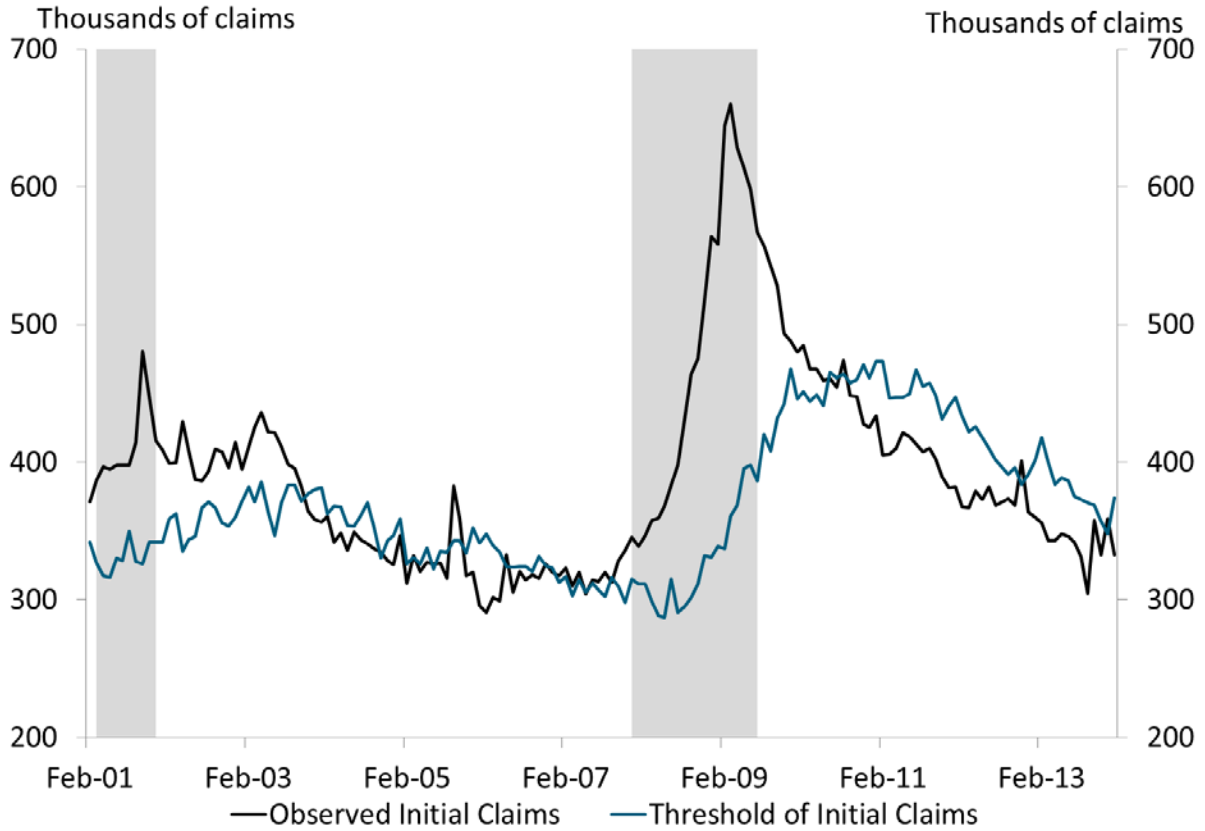
Note: Forecasts were generated between January 2004 and January 2014. Forecasts for the 400K deviation model were generated using the method described in the text and equation 12. The ARIMA model is estimated on the level of the unemployment rate, with the parameters selected by the BIC. The AR models are estimated on the monthly change in the unemployment rate. The RMSFE for each forecasting model were calculated using equation 10. The relative RMSFE for a model is the RMSFE of that model relative to the RMSFE of the random walk model.

Table 5: Forecasting Results During the Great Recession

Model:	RMSFE	Relative RMSFE
Week 1 Deviation from Threshold	0.1629	0.5082
Week 2 Deviation from Threshold	0.1597	0.4982
Week 3 Deviation from Threshold	0.1577	0.4918
Week 4 Deviation from Threshold	0.1549	0.4833
Final Week Deviation from Threshold	0.1521	0.4746
AR(1)	0.2913	0.9088
AR(1) w/ Week 1 Deviation from Threshold	0.1588	0.4953
AR(1) w/ Week 2 Deviation from Threshold	0.1539	0.4800
AR(1) w/ Week 3 Deviation from Threshold	0.1510	0.4711
AR(1) w/ Week 4 Deviation from Threshold	0.1449	0.4521
AR(1) w/ Final Week Deviation from Threshold	0.1401	0.4371
AR(4)	0.2113	0.6592
AR(4) w/ Week 1 Deviation from Threshold	0.1448	0.4518
AR(4) w/ Week 2 Deviation from Threshold	0.1382	0.4310
AR(4) w/ Week 3 Deviation from Threshold	0.1342	0.4186
AR(4) w/ Week 4 Deviation from Threshold	0.1274	0.3975
AR(4) w/ Final Week Deviation from Threshold	0.1223	0.3814
Week 1 400K Deviation	0.2539	0.7920
Week 2 400K Deviation	0.2517	0.7852
Week 3 400K Deviation	0.2491	0.7769
Week 4 400K Deviation	0.2470	0.7705
Final Week 400K Deviation	0.2445	0.7626
ARIMA(4,0,4)	0.2161	0.6742
Random Walk Model	0.3206	1.0000

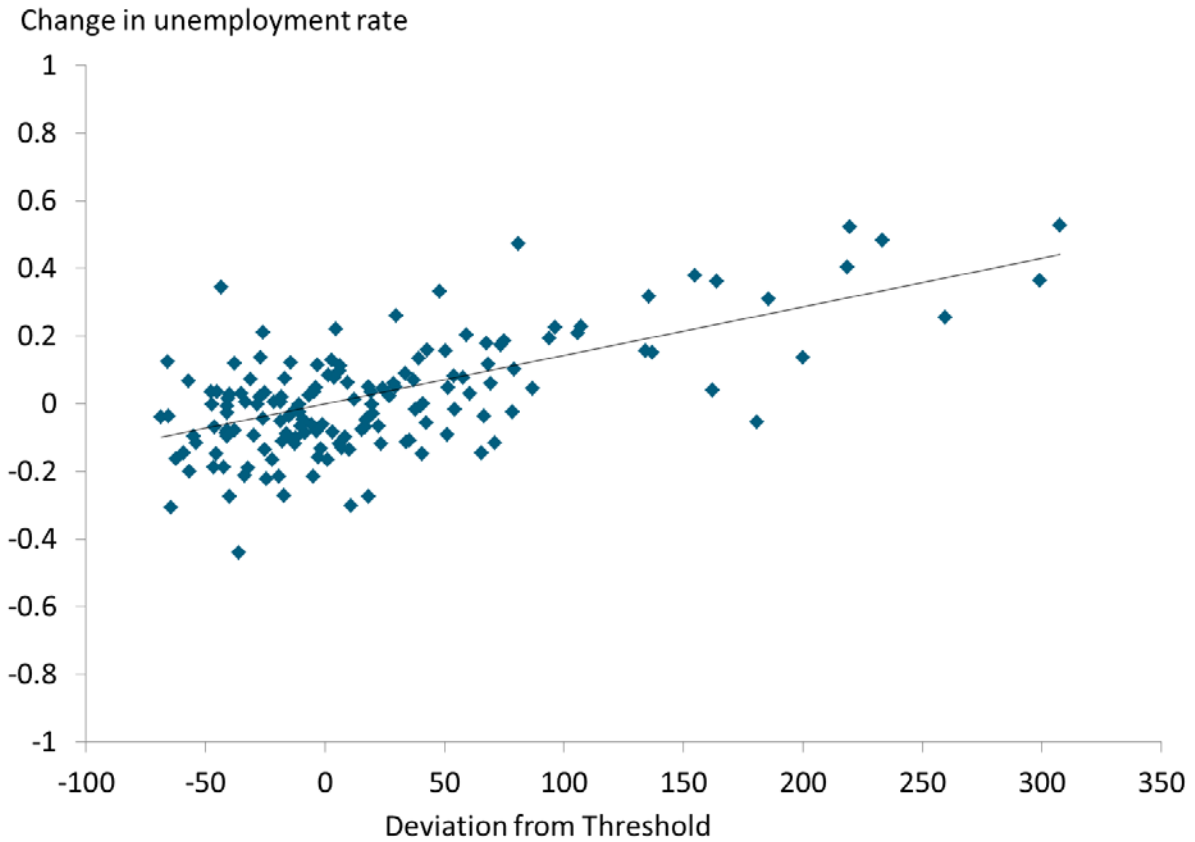
Note: Forecasts were generated between January 2008 and June 2009. Forecasts for the deviation model were generated using the method described in the text and equation 9. The AR models are estimated on the monthly change in the unemployment rate. Forecasts for the 400K deviation model were generated using the method described in the text and equation 12. The ARIMA model is estimated on the level of the unemployment rate, with the parameters selected by the BIC. The random walk model assumes that the unemployment rate in month t will be same as in month $t - 1$. The RMSFE for each forecasting model were calculated using equation 10. The relative RMSFE for a model is the RMSFE of that model relative to the RMSFE of the random walk model.

Figure 1: Threshold of Initial Jobless Claims



Note: The threshold of initial jobless claims comes from equation 7, and initial jobless claims correspond to the four week moving average of initial jobless claims from the fourth week of each month. Gray bars denote NBER recession dates.
Source: Bureau of Labor Statistics and author's calculations.

Figure 2: Deviations from the Threshold and Unemployment Change

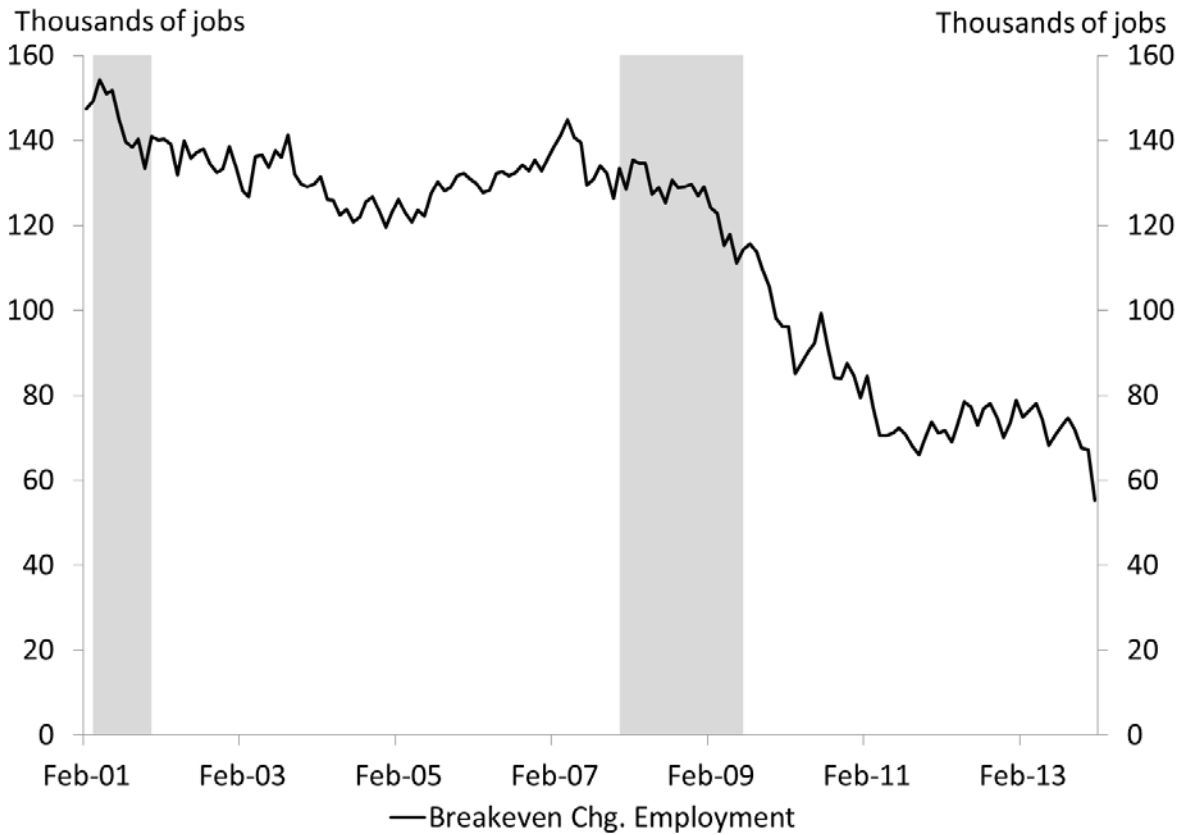


Note: The deviation from the threshold of initial claims is equal to the observed four week moving average of initial jobless claims in the fourth week of the month minus the threshold of initial jobless claims. The change in the unemployment rate is the first difference in the monthly unemployment rate. Observations are from February 2001 through January 2014.

Source: Bureau of Labor Statistics and author's calculations.

VII: Appendix

Appendix Figure 1: Breakeven Change in Employment



Note: The breakeven change in employment represents the change in employment in the CPS needed for the unemployment rate to remain constant, and is estimated using equation 5. The breakeven change in employment is then exponentially smoothed to minimize the in-sample sum of squared forecast errors. Gray bars denote NBER recession dates.