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A FLOW-BASED APPROACH TO REAL-TIME UNEMPLOYMENT PROJECTIONS

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ABSTRACT

This paper presents a flow-based methodology for real-time unemployment rate projections and shows that this approach performed considerably better at the onset of the COVID-19 recession in the spring 2020 in predicting the peak unemployment rate as well as its rapid decline over the year. It presents an alternative scenario analysis for 2021 based on this methodology and argues that the unemployment rate is likely to decline to 5.4 percent by the end of 2021. The predictive power of the methodology comes from its combined use of real-time data with the flow approach.

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1 Introduction

The longest labor market expansion in post-war US history came to an abrupt end with the emergence of the COVID-19 pandemic in March 2020. The unemployment rate jumped up from its historically low level of 3.5 percent in February to 14.7 percent in April. The path of the unemployment rate since then has puzzled many. Despite high numbers of weekly initial claims, the unemployment rate started to decline rather quickly and had declined by 7 percentage points, to 6.7 percent, in December 2020. Figure 1 presents the actual path of the unemployment rate and monthly consensus expectations over time since the beginning of the pandemic. Every month since April, the actual unemployment rate release turned out to be lower than the consensus expectation of professional forecasters.[1] The difference is particularly stark for early months of the pandemic. For example in May, the consensus expectation was 19.8 percent while the actual unemployment rate was 13.3 percent, down from April's peak of 14.7 percent. In this paper, we argue that from a flows perspective, neither the extent of the initial spike nor the rapid decline in the unemployment rate was a surprising outcome.

This paper presents a simple methodology for real-time unemployment rate projections and shows that this approach performed considerably better in 2020 at the onset of the COVID-19 recession. We then provide unemployment projections and an alternative scenario analysis for 2021 based on the methodology we build using real-time data.

Our methodology builds on earlier work that emphasized the importance of a flow-based approach in better understanding the evolution of the unemployment rate.[2] To this end, we first introduce the concept of an *unemployment possibility frontier*. This frontier restricts the potential paths of the unemployment rate to only plausible ones using historical estimates of flows as well as exploiting unemployment's internal dynamics. To show the importance of exploiting the unemployment possibility frontier, we first compute the unemployment

[1] Note that the consensus expectation for each month reflects the available data up to that month.
[2] Elsby et al. (2013), Barnichon and Nekarda (2012), Şahin and Patterson (2013), Meyer and Tasci (2015).

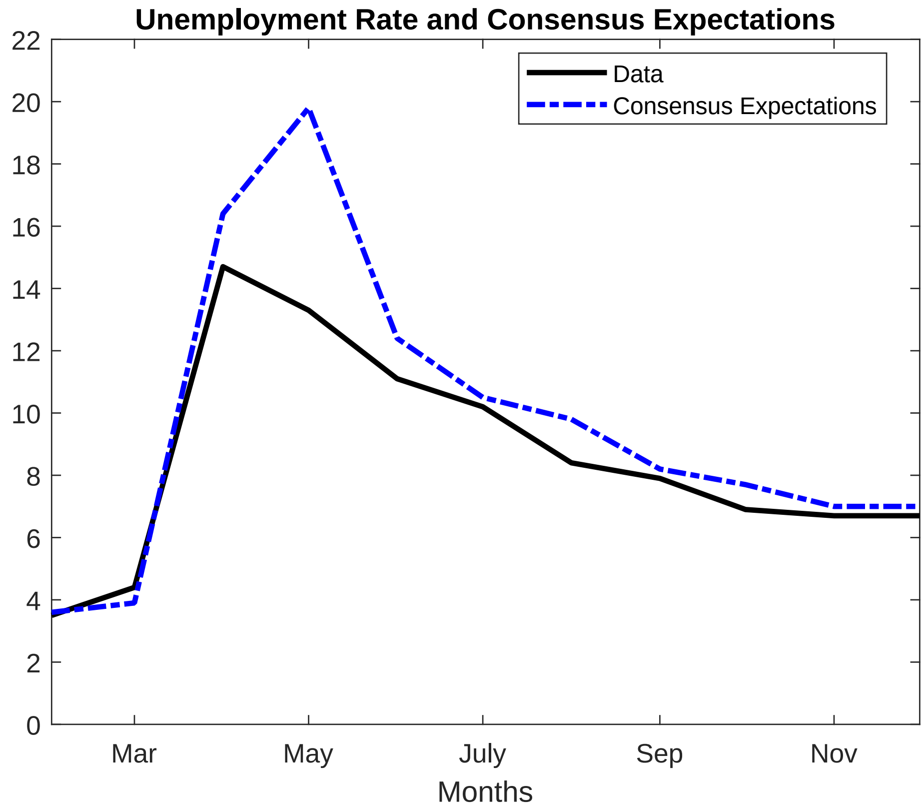


Figure 1: Monthly unemployment rate consensus expectations versus data. Source: Econoday employment report consensus figures collected from SNL news articles found in Factiva.

possibility frontier for June 2020 using data only available in April 2020. We show that this method implied a relatively quick adjustment in the unemployment rate conditional on a partial re-opening of the economy. In a note published during this early phase of the pandemic, we argued that a more likely path would see the unemployment rate peak around 15.8 percent in May followed by a gradual decline to end the year around 7.5 percent (Şahin et al. (2020)). In retrospect, our flow-based approach seems to have provided us with a more accurate projection than some alarmist forecasts at the time as well as the consensus expectations.

We then compute the unemployment possibility frontier for the first quarter of 2021 and show that the unemployment rate is likely to continue to decline unless there is a broad-based shutdown of the economy. We argue that the winter peak in infections in a subset of states that would bring more restrictions might cause a jump in the unemployment rate above 10 percent.

In the second part of our paper, we develop a flow-based approach for unemployment forecasts using real-time data. We do so in two steps: first we provide a mapping from initial claims for unemployment insurance to the unemployment inflow rate and a mapping from vacancy data to the unemployment outflow rate. This method is easy to implement using real-time data at any point in the business cycle. We use forecasts of flow rates directly for the first quarter of the forecast horizon. For longer horizons we use the method developed in Meyer and Tasci (2015) and condition our forecasts of flows on the output forecasts. We end with unemployment forecasts for 2021 and present several alternative scenarios. We conclude by examining the timing of the normalization in the unemployment rate back to its natural rate.

Section 2 introduces the flow accounting framework and develops the unemployment possibility frontier. It presents the frontier for June 2020 and January 2021. Section 4 develops a methodology for real-time unemployment projections and presents projections under alternative scenarios. Section 5 shows alternative timing of the normalization of the unemployment rate to its natural rate.

2 The Unemployment Possibility Frontier

Our empirical approach builds on a large literature that links unemployment fluctuations to individual flow rates that contribute to net changes in the unemployment stock.[3] Intuitively, at any given time period t, there will be inflows into the unemployment stock at rate s_t and some outflows at rate f_t. At the heart of this approach lies the simple equation of motion

[3] See Shimer (2005, 2012), Elsby et al. (2009), Elsby et al. (2013), Elsby et al. (2015), and Fujita and Ramey (2009), among others

for the unemployment rate that is a function of these hazard rates:

$$U_{t+1} = \beta_t U_t^* + (1 - \beta_t) U_t \tag{1}$$

where $\beta_t = 1 - e^{-(s_t + f_t)}$ and $U_t^* = s_t/(s_t + f_t)$. The flow rates, f_t and s_t, can be computed following the methodology proposed by Shimer (2005) using publicly available aggregate data on unemployment, short-term unemployment, and the labor force.[4] Equation 1 can then be used to obtain a projection for future unemployment rates if one has forecasts in hand for the flow rates, f_t and s_t. In fact, Barnichon and Nekarda (2012) and Meyer and Tasci (2015) show that such an approach yields forecast improvements for the near term and medium term for unemployment forecasting, respectively.

The challenge in the current context is to have forecasts for these flow rates. Both Barnichon and Nekarda (2012) and Meyer and Tasci (2015) use statistical methods to forecast inflow and outflow rates, methods that are heavily informed by the historical correlations in the data. As became clear in the early weeks of the pandemic, history can hardly play its usual informative role in the current environment, at least in the near term. There is substantial uncertainty about the course of the pandemic and hence the aggregate economy and the labor market. To address this issue, we propose a two-pronged approach. First, we use equation 1 to consider a feasible set of unemployment realizations given hypothetical flow rates, f_t and s_t. This helps us discipline our judgment about the plausible scenarios for these rates in the near term. We complement this with alternatives where we project an outflow rate, f_t, using a matching function, and an inflow rate, s_t, using the data on initial claims in Section 3. Having obtained forecasts of f_t and s_t in the near term from this reduced-form empirical approach, we then implement a forecasting exercise beyond the near term following Meyer and Tasci (2015).

[4] Note that this approach yields an estimate for the flow rates that lags the unemployment data by a month. For example, if the last data available for the unemployment rate are for March, the last estimate for the flow rate we can compute using Shimer's (2005) methodology is for the month of February.

2.1 Defining the Unemployment Possibility Frontier

Given the unprecedented nature of the COVID-19 shock to the labor market, it is hard to rely on historical data to make accurate projections. That is why we develop a reverse strategy by asking what values of f_t and s_t would produce a particular unemployment rate forecast and then compare the resulting values with their historical ranges. We illustrate these calculations in a display we call an *unemployment possibility frontier*. This exercise provides useful insights about the plausible paths of the unemployment rate over a set of upcoming months.

More formally, for any given initial level of the unemployment rate, u_t, we can use Equation 1 and obtain a predicted unemployment rate for the next month, $\overline{u}$, with a particular combination of f_t and s_t. In principle, there are infinitely many combinations of f_t and s_t that would bring unemployment from u_t to $\overline{u}$. Assuming constant flow rates, one can generalize this for a k-periods-ahead unemployment rate and define the unemployment possibility frontier as:

$$UPF_{t+k}^{\overline{u}}|u_t = \{(f,s) : \beta U^* \sum_{j=0}^{k} (1-\beta)^{j-1} + (1-\beta)^k u_t = \overline{u}\} \tag{2}$$

where $\beta = 1 - e^{-(s+f)}$ and $U^* = s/(s+f)$.

We next compute the unemployment possibility frontier for June 2020 using data only available as of March 2020 to show its usefulness at the beginning of the COVID-19 recession. We then apply the same methodology to compute the unemployment possibility frontier in March 2021 given the available data as of December 2020.

2.1.1 Unemployment Possibility Frontiers at the Onset of the COVID-19 Recession

Figure 2 displays unemployment possibility frontiers for June 2020, given the unemployment rate in March, at the beginning of the pandemic. The unemployment rate was reported to be

4.4 percent for March, and many observers and analysts were worried that the US economy would enter a severe labor market downturn, bringing the unemployment rate to above 20 percent within a few months. We present several possibilities for the June unemployment rate, including these extreme cases. Aside from trivial natural bounds for f and s, we restrict our attention to historically feasible ranges for f and allow for clearly extreme values for s.[5] To provide some context, we indicate the historical realizations of f and s from two recessionary episodes and the overall sample range along with the unemployment possibility frontiers.

Figure 2 highlights several interesting points about the feasible unemployment rate dynamics we should expect. First, a typical severe recessionary dynamic (similar to the Great Recession or the early 1980s experience) could have brought the unemployment rate above 6 percent easily within three months but would not be able to bring it up to 15 percent at all.[6] Second, as the three data points in Figure 2 show, actual realizations of f and s stayed within the historical range with the exception of the March flow rates. For example, the inflow rate for March, s_t, was 0.116, more than double the highest inflow rate we had recorded until that point, at 0.051. Similarly, f_t for March stood at 0.081, less than 40 percent of the lowest outflow rate we had in the data prior to March. The simple message of this exercise is very informative. In retrospect, it should have been almost impossible to reach 25 percent unemployment after two to three months of severe labor market stress.

Our illustration of the unemployment possibility frontier for June 2020 (looking from March) also underscores how the fluidity of the US labor markets alleviated the impact of the initial shock relatively quickly. As Figure 2 shows, any realizations of the flow rates that fall within the historical range would have kept the unemployment rate under 15 percent,

[5] Since f is typically procyclical, considering f values better than the historical records is not plausible in light of the unprecedented negative shock. Similarly, since s is strongly countercyclical, we have to consider the possibility of unprecedented levels for s in order to be consistent with the large number of unemployment insurance claims.

[6] In fact, the historical range does not support anything beyond 13 percent for June using our method, that is, if we had assumed the worst possible historical realizations for f and s: the lowest f and the highest s in the data.

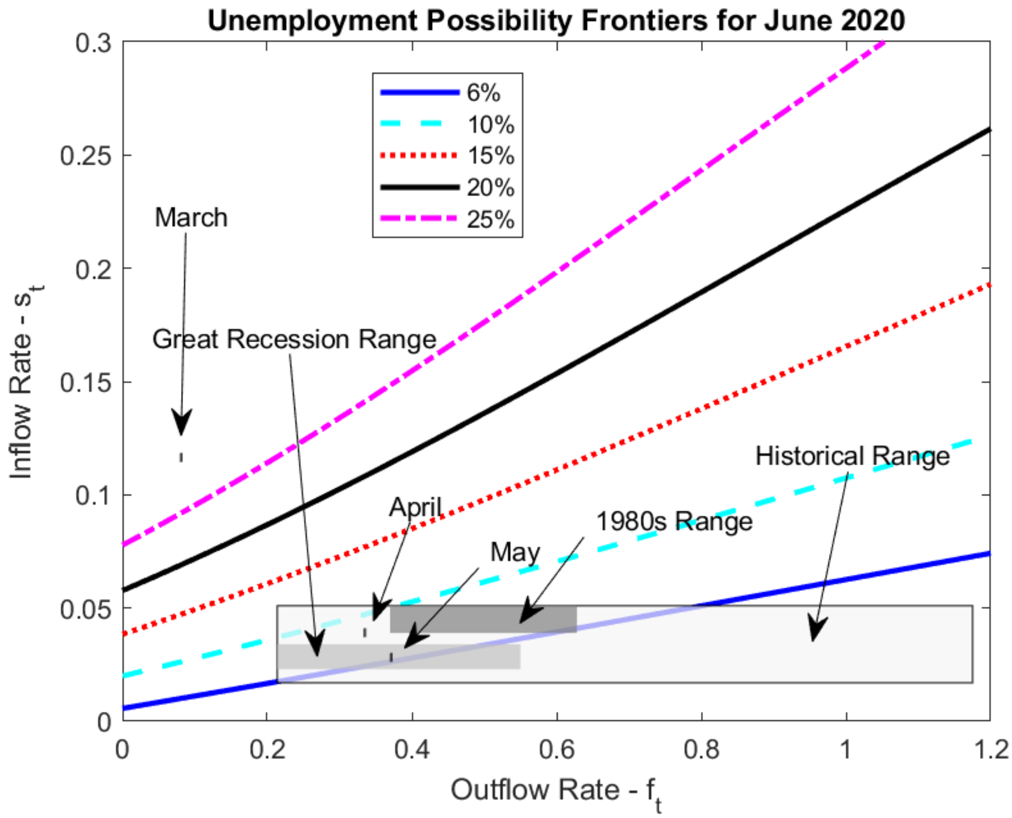


Figure 2: Unemployment possibility frontiers for June given March 2020 unemployment rate. Shaded areas indicate the range of f and s realizations during business cycles that include 1980s recessions and the Great Recession. The rectangular box includes all historical realizations through February 2020.

as long as the worst of the effects of the COVID-19 pandemic were over before June. This analysis shows that the unemployment possibility frontier is particularly powerful in times of extreme labor market disruptions such as in early 2020. The consensus expectations about the unemployment rate during the early days of the pandemic and the initial wave of economy-wide shutdowns were pretty bleak. Throughout the month of March, 10.7 million new claims were filed for unemployment insurance in the US, followed by 20.2 million new claims in April. These unprecedented levels of initial claims fueled the dire expectations about a possible 20 percent unemployment rate in May. However, examining the state of the labor market in March 2020 shows how natural limits on the potential values for the underlying flow rates implied a peak in the unemployment rate that is around 15 percent instead of 25 to 30 percent as speculated by many.[7]

2.1.2 Unemployment Possibility Frontiers for March 2021

Data since than have been mostly in line with our expectations and the unemployment rate has declined quite substantially from its peak in April. Analyzing the unemployment possibility frontiers from the current state of the labor market onward might similarly inform us about the potential evolution of the unemployment rate during the *recovery* process. Figure 3 displays the unemployment possibility frontiers for March 2021, given the unemployment rate in December. There is a wide range of possibilities for the March level. Even if we experience realizations in the flow rates that fall in line with the outcomes we observed during the Great Recession, we expect the unemployment rate to be between 5 percent and 10 percent. If we assume that the flow rates until then will be exactly the same as the averages we have registered since April, then the unemployment rate will be 6.9 percent as the corresponding unemployment possibility frontier indicates in Figure 3, essentially staying at the level of October. This happens to be very close to the real-time projection that Şahin et al. (2020) presented in May.

3 Real-time Unemployment Projections

We have shown that the path of the unemployment rate is determined by the inflow and outflow rates and unemployment's internal dynamics. We argue that forecasting unemployment flows and using unemployment's inherent dynamics summarized in Equation 1 provide a more accurate assessment than trying to forecast the unemployment rate on its own. In this section, we build on this insight and use real-time data on unemployment insurance claims and vacancies to develop projections for unemployment flows.

Figures 4a and 4b show the evolution of inflow and outflow rates from 1948 to 2019. As

[7] Examples of projections warning about a Great Depression-level unemployment rate were abundant both in the business press and among economists. See, for instance, Ivanova (2020), Jones (2020), Wenger and Edwards (2020), and Faria-e-Castro (2020), among others.

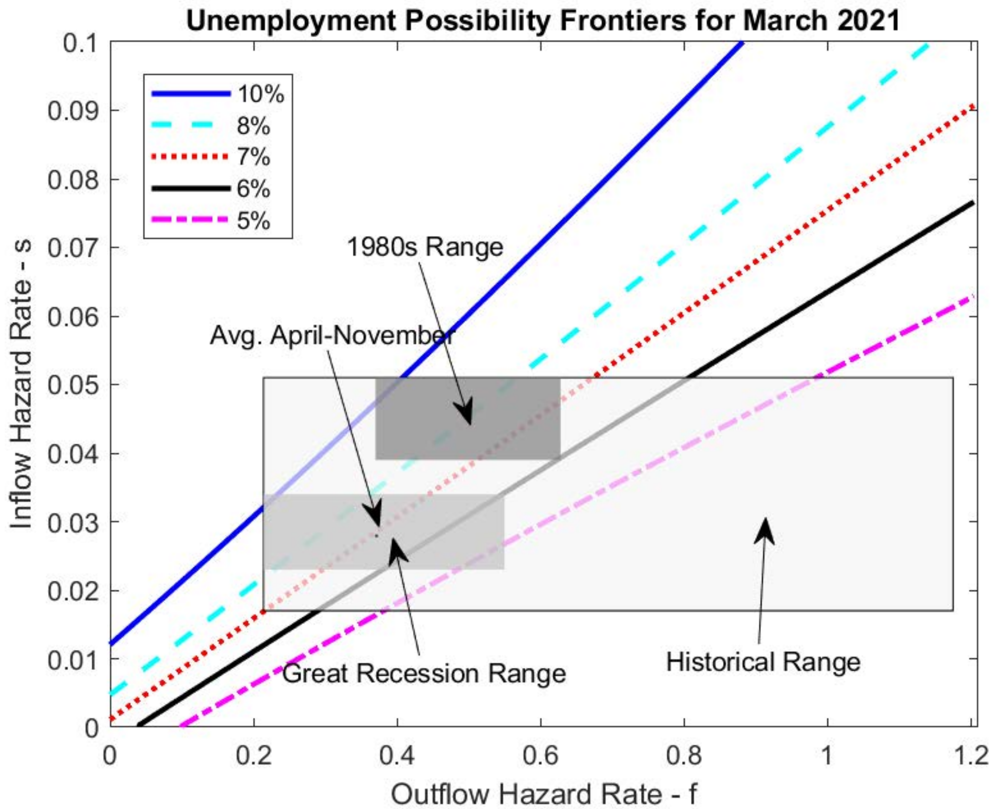
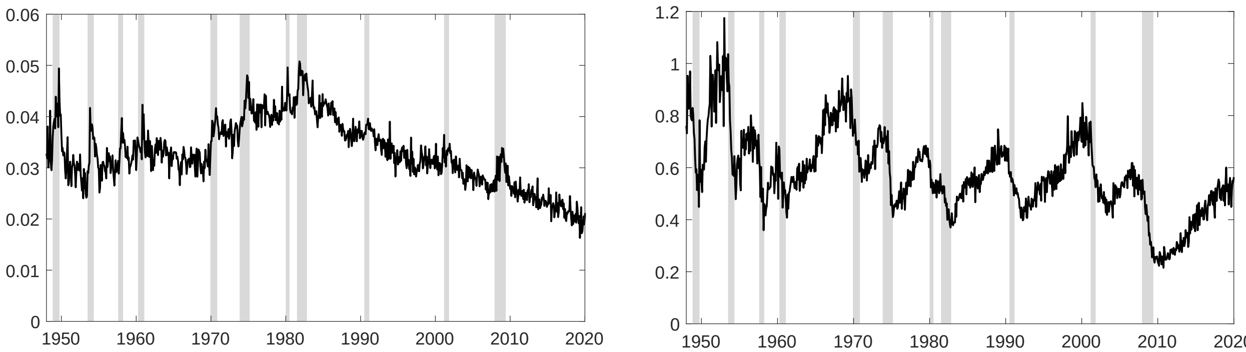


Figure 3: Unemployment possibility frontiers for March given December 2020 unemployment rate. Shaded areas indicate the range of f and s realizations during business cycles that include 1980s recessions and the Great Recession. The rectangular box includes all historical realizations through February 2020.

the figures show, the cyclical and trend evolutions of inflow and outflow rates are drastically different. The unemployment inflow rate exhibits sharp, short-lived spikes at the onset of recessions, while the unemployment outflow rate exhibits prolonged procyclical movements. In addition, while there is an unmistakable downward trend in the inflow rate, the outflow rate has been trending down only mildly.

Given flow dynamics over the business cycle, the unemployment rate at the onset of recessions is heavily affected by the inflow rate. On the contrary, once the spike in the inflow rate subsides, unemployment dynamics are almost solely driven by the outflow rate. This is



(a) Inflow rate, s

(b) Outflow rate, f

Figure 4: Inflow and outflow rates (1948-2019)

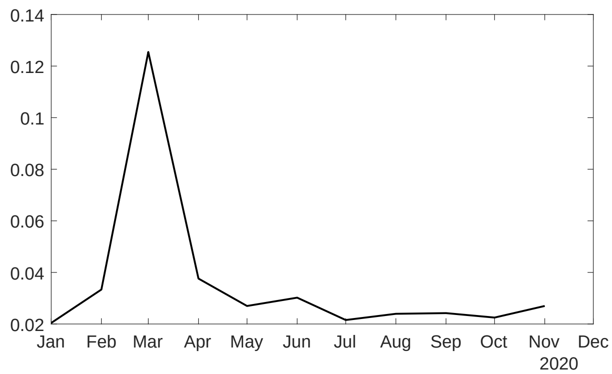
a key insight that helps us accurately assess unemployment fluctuations.[8]

3.1 Forecasting Unemployment at the Onset of the COVID Recession

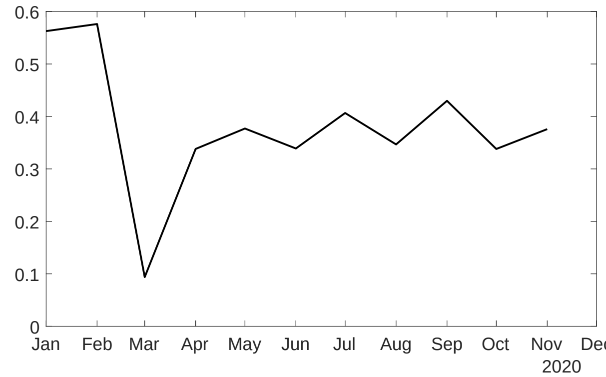
Figures 5a and 5b show the evolution of the unemployment inflow rate starting in January 2020. While we experienced an unprecedented spike in the inflow rate that coincided with the shutdowns, the spike had subsided by the end of the year. This figure suggests that forecasting the unemployment rate accurately at the onset of the recession required predicting the severity of the spike. In this subsection, we revisit Şahin et al. (2020), where we used real-time releases of initial claims for unemployment insurance in April 2020 to estimate the path of the unemployment rate. This particular episode showcases the superiority of the flow approach. After we discuss the beginning of the recession, we turn to December 2020 and provide a flow-based forecast for 2021.

An important real-time data source that is informative about unemployment inflows in the economy is unemployment insurance claims. The initial claims report, produced by the Bureau of Labor Statistics (BLS), is a count of the number of individuals who have lost their jobs and applied for unemployment benefits. Applications for these benefits are managed by individual states and eligibility requirements as well as the level of compensation vary.

[8] Once again, by no means is this our novel insight. Several studies before us highlighted this pattern over the business cycle: Shimer (2005, 2012), Elsby et al. (2009), Elsby et al. (2013), Meyer and Tasci (2015) and Crump et al. (2019).



(a) Inflow rate, s



(b) Outflow rate, f

Figure 5: Inflow and outflow rates in 2020

States report the number of applications they receive weekly, and the BLS aggregates this information with a weekly news release. It is tempting to interpret this number as a rise in the number of workers who are unemployed (the stock of unemployed) and use it to forecast the unemployment rate for the upcoming month.

Consider implementing this idea for the month of April 2020. The sum of all of the initial claims filed after the March reference date for the unemployment survey (CPS) until the April reference date equals 22 million. Adding this to the stock of unemployed in March (7 million) brought the stock to 29 million. Even if we assumed that the labor force did not decline from its March level (163 million), this logic would yield an 18 percent unemployment rate. If one considered a potential decline in the labor force or that not all unemployed workers would have been eligible (or have chosen to file) for unemployment insurance, the unemployment rate prediction would have been higher than 18 percent. In the end, April's unemployment rate was reported to be 14.7 percent despite a sharp decline in the labor force (down to 156 million). This real-time example highlights the potential pitfalls of using stocks to project an unemployment rate.

More specifically, this approach provides a static view of the labor market. In reality, the US labor market is fluid, with many workers flowing into and out of unemployment in a given month. One way to quantify this large turnover, albeit from the employers' perspective, is to look at the labor turnover measures from the BLS' Job Openings and Labor Turnover Survey (JOLTS). During March and April, around 14.6 million and 10 million workers, respectively, separated from their employers, compared to an average of 5.6 million in 2019, highlighting the severe impact of the early mitigation efforts and shutdowns. However, even when an important segment of economic activity was shut down during those two months, there were 5.1 million and 4 million new hires, respectively, for March and April, in contrast to a monthly average of 5.8 million recorded in 2019.

Another potential problem with this approach pertains to the informative nature of the initial claims about the incidence of unemployment. Not all unemployed workers would be eligible for benefits and even if they are, they do not always file a claim. The pandemic environment and the accompanying government efforts to alleviate the costs might have also changed the composition of the pool of who files claims. Under the Coronavirus Aid, Relief and Economic Security (CARES) Act, benefits were expanded to include higher compensation and newly eligible groups such as individual contractors and the self-employed. Thus, the large numbers of claimants reported in the early months of the pandemic may not reflect the true extent of workers flowing into unemployment.[9]

In Figure 6 we plot the unemployment inflow rate together with initial claims. To make the series comparable, we define the initial claim rate as the ratio of the monthly total of initial claims to covered employment. While there is a striking comovement between the two series, they display differences in levels and cyclicality that arise from time variation in unemployment insurance eligibility, take-up rates, and movement into unemployment from out of the labor force. The time variation in these factors is captured by the inflow rate but not by initial claims as discussed in Hobijn and Şahin (2011). To estimate the relationship between the rates more accurately given these differences, we run a regression of the form

$$log(s_t) = \beta_0 + \beta_1 log(Initial\ Claims_t / Covered\ Employment_t) + \epsilon_t \tag{3}$$

[9] Cajner et al. (2020) provide an insightful analysis of the unemployment claims during this episode and how to reconcile them with the job losses

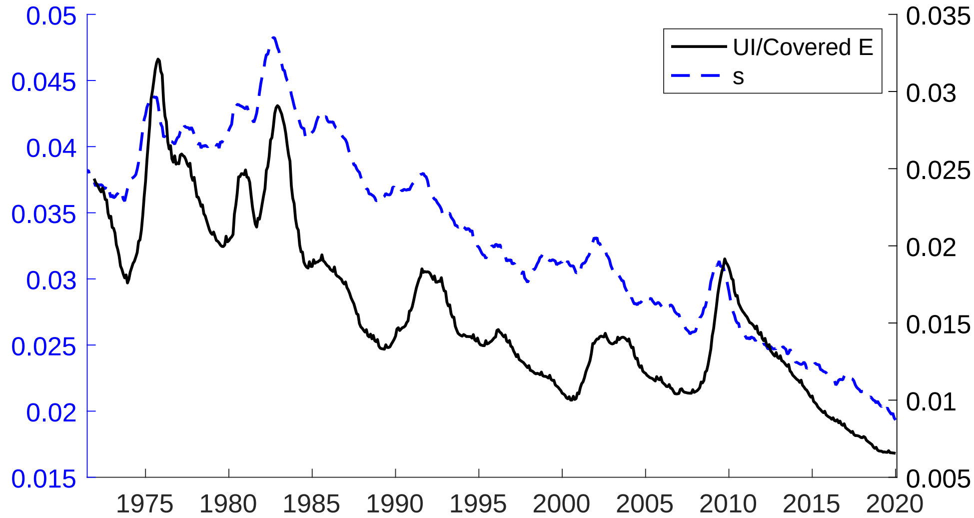


Figure 6: Unemployment inflow rate and monthly initial claims as a fraction of covered employment (12-month moving average)

where s is the inflow rate and initial claims and covered employment are in levels. We run this regression using data from January 1970 to February 2020 and report the results in Table 1.

	$log(f)$
log(initial claims/covered employment)	0.503^{***}
	(0.013)
Observations	590
R^2	0.706

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors in parentheses.

Table 1: OLS estimation results for the relationship between initial claims and the unemployment inflow rate.

This regression suggests that when the ratio of initial claims to covered employment rises by 1 percentage point, the inflow rate typically rises by 0.5 percentage points. We use these regression results to translate a path of initial claims into a path of the inflow rate. The path of initial claims must also be estimated, and we do this through mid-June by taking the initial claims data from the week ending March 21 to the week ending April 25 and projecting the path forward based on the following two assumptions. First, we assume that all the workers identified by Leibovici et al. (2020) as having the highest risk of layoff or unemployment will have filed for unemployment insurance by mid-May. Second, we assumed in April 2020 that thereafter the path of initial claims will follow the path of sharp declines observed during the Great Recession, averaging around 600,000 and declining gradually to February levels by the end of the year.

As we have discussed, while the inflow rate is an important determinant of the peak unemployment rate, its importance dies away quickly. Consequently, the recovery in the unemployment rate depends on the evolution of the unemployment outflow rate, which exhibits a prolonged procyclical behavior. Since the outflow rate is mostly driven by job creation in the economy, we use a matching function framework to predict the evolution of the outflow rate. As Figure 7 shows, there is a tight comovement between labor market tightness and the outflow rate. We repeat our procedure for April 2020 and December 2020 *using data only available at the time of the forecast* to evaluate the usefulness of our method.

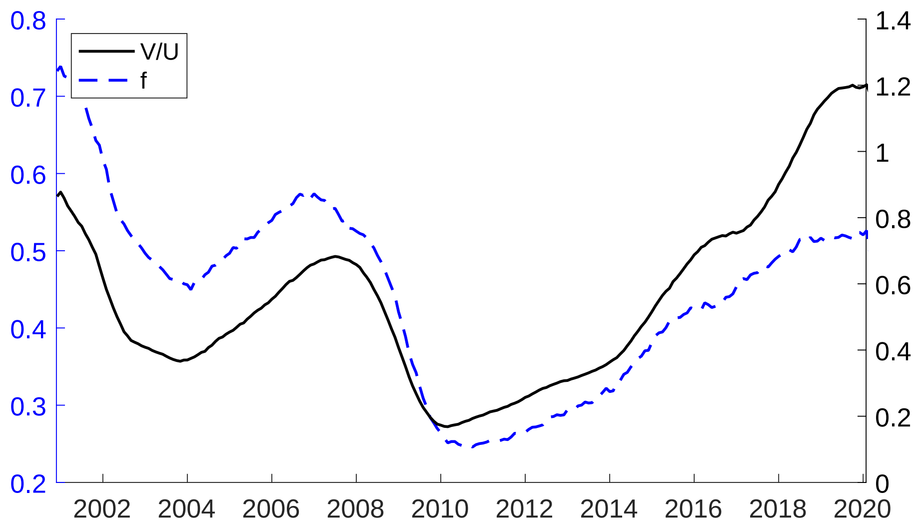


Figure 7: Labor market tightness (vacancy-to-unemployment ratio) and the outflow rate December 2000-January 2020 (12-month moving average)

We start by estimating a Cobb-Douglas matching function in the form of

$$H_t = \Phi U_t^{\alpha} V_t^{1-\alpha}$$

where H_t denotes hires, V_t vacancies, and U_t the number of unemployed. Dividing both sides by U_t results in a simple relationship between the outflow rate and market tightness V_t/U_t. We use data from December 2000 to February 2020 to estimate the relationship and report the results in Table 2.

	$log(f)$
$log(V/U)$	0.410^{***}
	(0.026)
Observations	232
R^2 height	0.513

Note: $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors in parentheses.

Table 2: Matching function estimation results.

We again go back to April 2020 and use the matching function framework to predict the evolution of the outflow rate at the onset of the recession. Recall that in April, the most recent available vacancy rate and the unemployment rate belonged to March, which showed only limited weakness due to the timing of the shutdowns. However, there were reports of mass hirings in essential work and e-commerce companies.[10] At that time we made the assumption that vacancies would drop by 50 percent relative to their February 2020 levels and remain at the level for the second quarter of 2020. Then using the matching function, we computed a predicted path for the outflow rate for each month and used the unemployment dynamics equation to compute the unemployment rate. Putting together our inflow and outflow rate assumption implied a peak unemployment rate of around 15.8 percent – similar to the actual peak of 14.7 percent as we show in Figure 8. We predicted the unemployment rate to decline to slightly above 7 percent at the end of 2020 and the actual unemployment rate was 6.7 percent at the end of the year. We also provided alternative scenarios in April 2020 for the effects of longer shutdowns which did not materialize in reality. These scenarios implied higher unemployment rate peaks close to 20 percent.

[10] https://www.challengergray.com/blog/2020-march-job-cut-report-222288-cuts-announced-march-most-jan-2009-covid/.

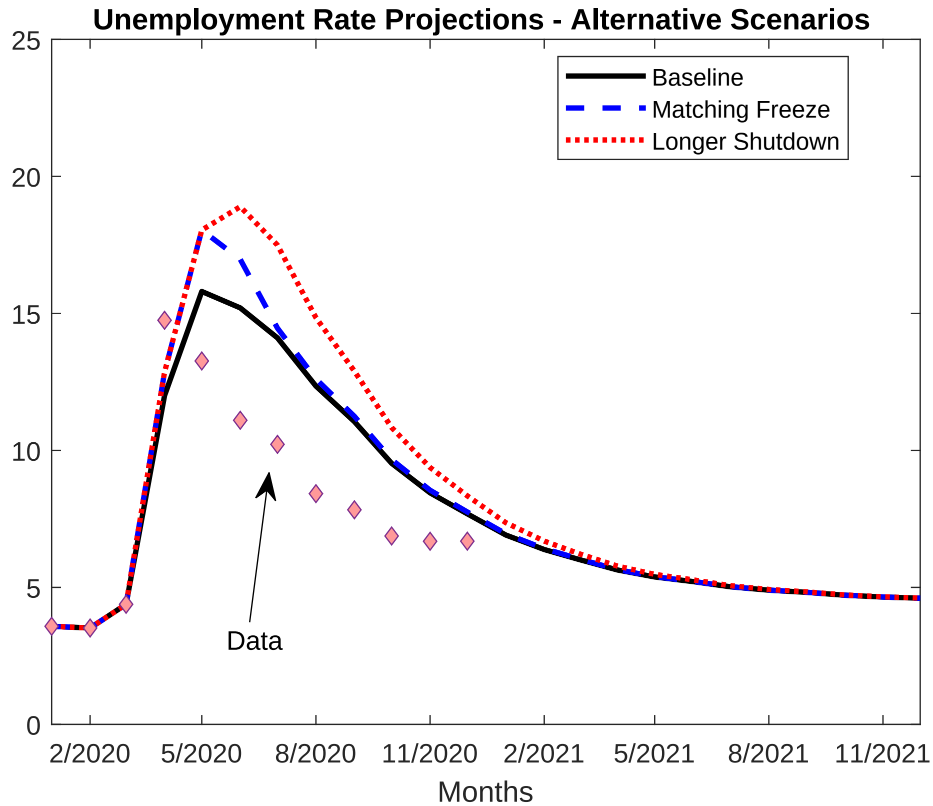
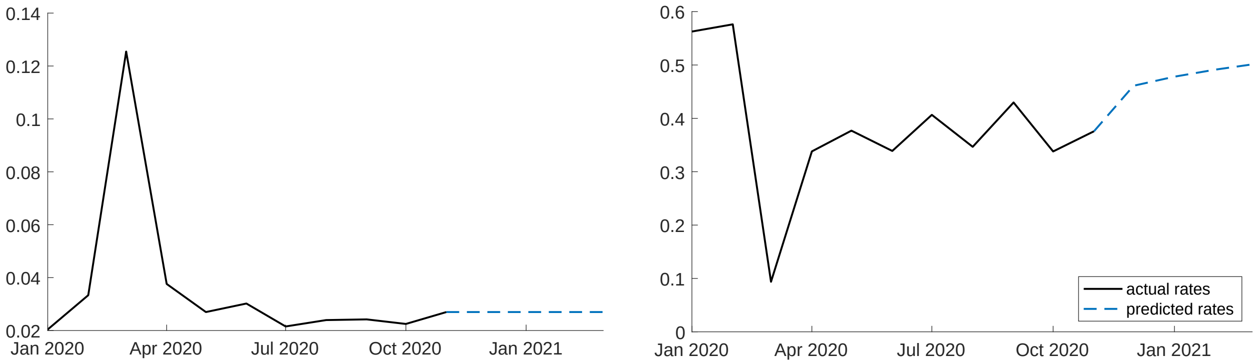


Figure 8: Unemployment rate projections using only real-time data available as of April 2020. See Şahin et al. (2020) for details.

3.2 Forecasting Unemployment Flows in 2021

As we have seen in Figures 5a and 5b, the unprecedented spike in the unemployment inflow rate subsided completely. Again this is a pattern that is common for all recessions. We make the assumption that unless there is a winter shutdown, unemployment inflows will remain at their current level in the next year and, going forward, will likely decline at a slow pace consistent with the aging of firms and workers in the economy. We make the assumption that vacancies will remain at their October level and use the matching function framework to compute the unemployment rate for 2021. Figures 9a and 9b show the implied path of inflow and outflow rates for 2021.

After obtaining the near-term forecasts for the flow rates in the current quarter using real-time data, we extend our projections relying on a more formal statistical approach.



(a) Inflow rate, s

(b) Outflow rate, f

Figure 9: Inflow and outflow rates in 2020 and our projections

In particular, we follow the literature and use the approach advocated in Meyer and Tasci (2015), who exploit a simple unobserved components model based on Tasci (2012), encompassing aggregate output and unemployment flows, f and s. In the model, the flow rates and the aggregate output (real GDP) have both random-walk trend and transitory cyclical components. The cyclical components of the flow rates depend on the cyclical component of output.

Meyer and Tasci (2015) show that this simple model can improve forecast accuracy relative to the VAR approach presented in Barnichon and Nekarda (2012), for certain forecast horizons beyond the very near term. Moreover, Meyer and Tasci (2015) argue that conditioning the aggregate output in the flow model in Tasci (2012) on professional surveys (e.g. Blue Chip (BC), Survey of Professional Forecasters (SPF), etc.) could further improve the forecast accuracy. As we have seen for our April 2020 projections, this approach is particularly relevant in the context of the COVID-19 shock, as the shock to aggregate output is unprecedented. Hence, in practice, we use the Blue Chip GDP consensus forecasts and condition the aggregate output process in the model as in Meyer and Tasci (2015) to follow a cyclical pattern to replicate the BC survey.[11]

We now summarize our projections for the unemployment rate over the next several quar-

[11] The underlying assumption is that the COVID-19 shock we experienced was a cyclical shock and did not cause a change in the trend of aggregate activity.

ters. Our baseline projections rely on the flow projections we obtained using unemployment initial claims and the matching function in the near term (December through March) as in Section 3.1 and the consensus GDP forecasts from the BC survey for the whole forecast horizon. Beyond the near term, the flow model generates the flow rates as in Meyer and Tasci (2015). We also provide an alternative scenario analysis.

First, we consider an alternative scenario where the flow rates for the four months in question will be the same as the average we experienced since April 2020. This scenario is intended to serve as a benchmark where the labor market operates similar to how it has been operating during the pandemic, with the exception of the large initial shock in March. Second, we present a scenario with a large-scale shutdown in the economy, similar to the shutdown we experienced in early 2020. This scenario assumes that f takes the values 0.46, 0.1, 0.47, and 0.49 for December, January, February and March, respectively. Similarly, s takes on the values 0.027, 0.1, 0.027, and 0.027.[12] Our final scenario assumes a shutdown pattern across states such that only the high-risk ones will shut down and economy-wide closures do not happen nationally. This scenario uses the predictions for new state-level mandates and restrictions from the University of Washington's Institute of Health Metrics and Evaluation (IHME) and assumes that about one-third of the US population will be living under these restrictions over parts of January.[13] In this scenario, the aggregate flow rates are assumed to be a weighted average of our baseline scenario (for two-thirds of the population) and the shutdown scenario for the remainder of the nation.

Figure 10 shows our unemployment projections for the baseline and alternative scenarios we described above. Our baseline forecast starts the year at 6.3 percent and gradually declines to 5.4 over the course of 2021. This path is similar to the path implied by the average flow rates we have experienced during the pandemic. Obviously, the main uncertainty about

[12] This scenario assigns the worst impact of another shutdown to January, following a similar pattern from March and April.

[13] IHME's predictions assume that states will re-impose mandates when daily death rates reach 8 per million. See IHME (2021), Figure 15 for a detailed map.

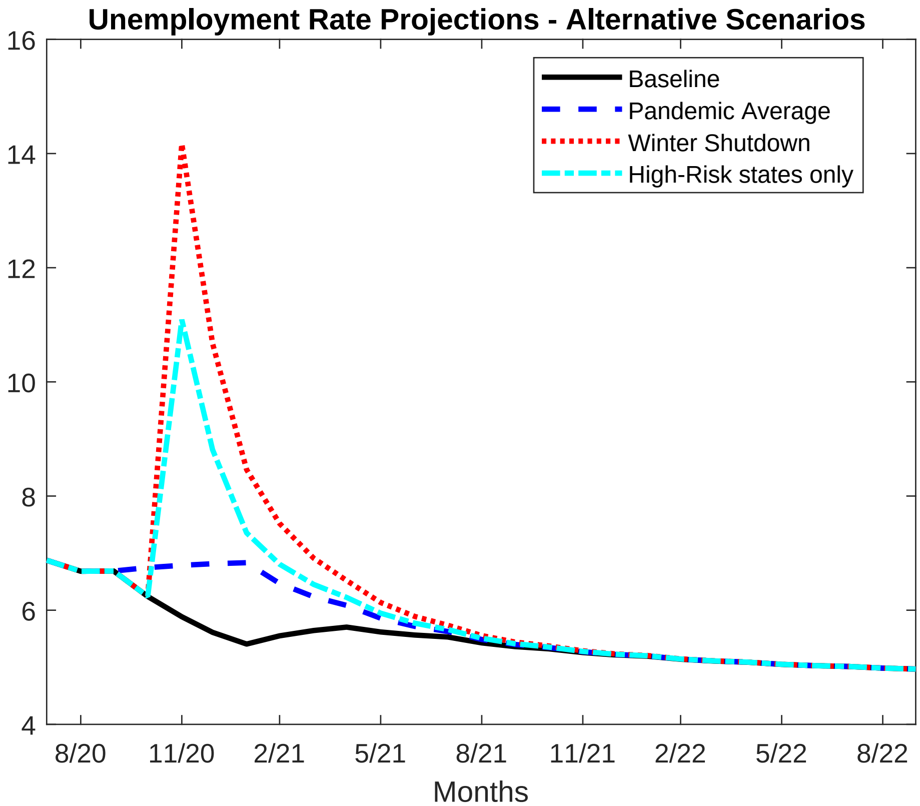


Figure 10: Unemployment rate projections under alternative scenarios

the unemployment path is related to the evolution of the outbreak and whether new restrictions on social and economic life would be imposed by public health authorities. A broad shutdown similar to the one we experienced in early 2020 could increase the unemployment rate up to 14.2 percent in February. A more targeted approach, where shutdowns occur only in states that are projected to be hard hit by the pandemic, would instead bring it up to 11 percent. Both of these scenarios also converge to 5.4 percent by the end of 2021.

All of our projections in Figure 10 assume that the overall economic growth follows the consensus forecast from the BC survey over the forecast horizon. However, even among survey participants in the BC survey, there is significant uncertainty about this path. To highlight how the cyclical "normalization" can affect the unemployment rate path, we also analyze the evolution of the unemployment rate under two extreme alternatives: the top 10 percent and the bottom 10 percent of the forecast distribution. Figure 11 shows the impact of the underlying assumption for the GDP path. Differences in the most optimistic and the most pessimistic ends of the BC distribution imply a variation of as much as 3 percentage points at the end of 2021. Note that the unconditional forecast corresponds to the case in which output evolves endogenously from the current quarter on, within the flow model. Since the shock over the past three quarters created a large output gap at the end of the sample period, the model's internal prediction is an output recovery stronger than even the most optimistic BC forecast.

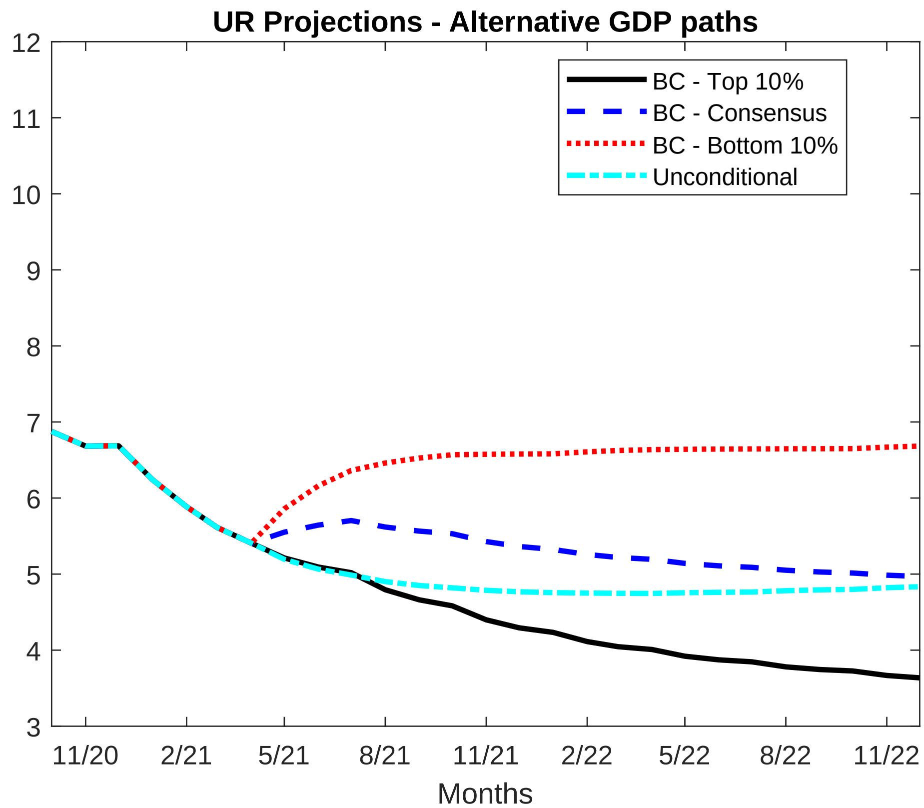


Figure 11: Unemployment rate projections under different GDP growth projections

4 When Will the Unemployment Rate Go Back to 4.1 Percent?

Starting the year at 6.7 percent might indicate some normalization for the US labor markets, but it would still leave us far from where we were before the COVID-19 shock. Even though pre-pandemic levels of the unemployment rate were exceptionally low by historical standards, estimates of what constitutes the natural rate of unemployment or the long-run level consistent with the underlying trends stood around 4 percent at the time.

FOMC participants in December 2020 released their long-run projections for the unemployment rate, as part of the quarterly Summary of Economic Projections (SEP), and the midpoint of the central tendency was reported to be 4.1 percent. An important input for policy is: How likely is it for the unemployment rate to reach 4.1 percent in the near future, given where we are today? Figure 12 displays our answer to this question using our framework.

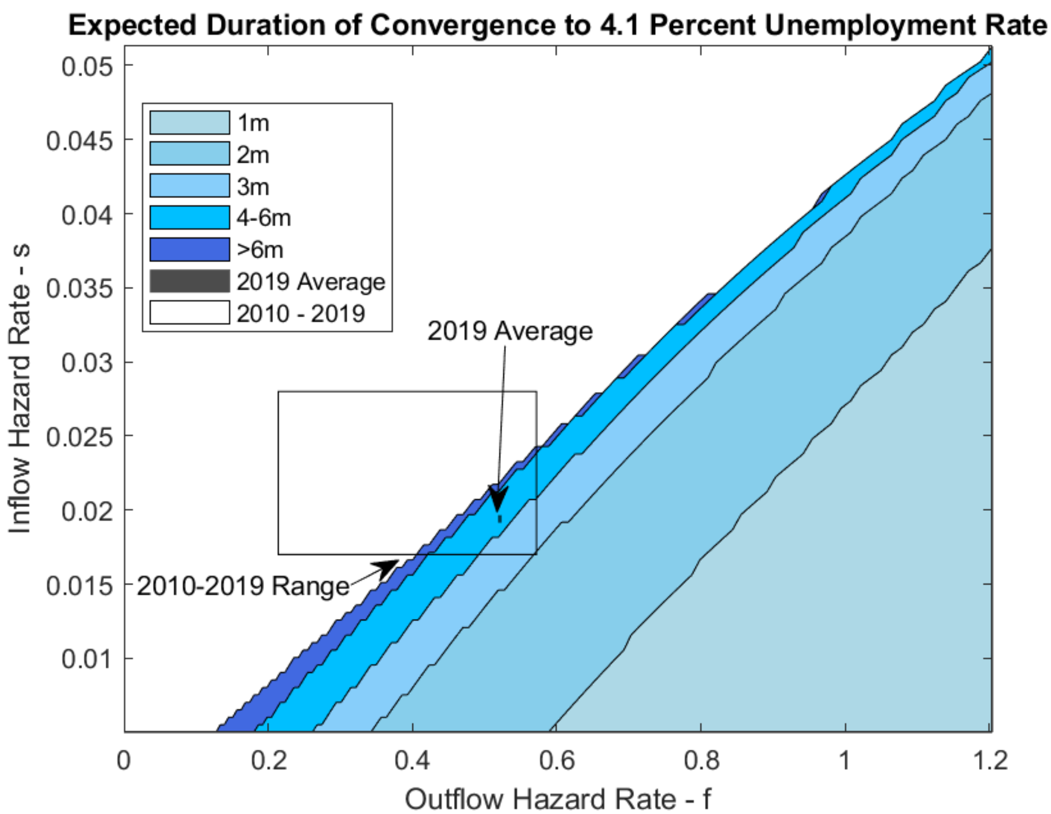
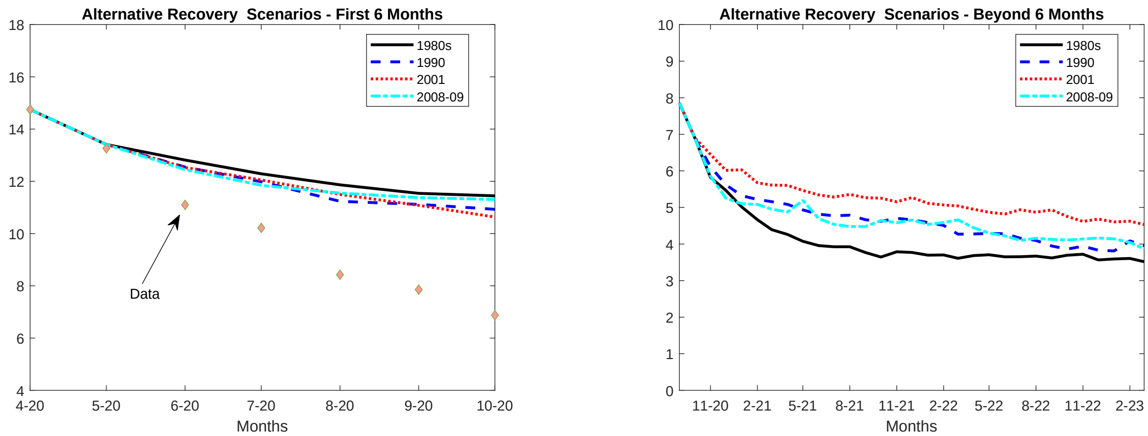


Figure 12: Expected duration of convergence to 4.1 percent unemployment rate; midpoint of the long-run SEP for the unemployment rate (FOMC-December 11, 2020). The rectangular area indicates the range of f and s realizations during the last labor market recovery starting in 2010.

We simulate the evolution of the unemployment rate using Equation (1) going forward from its current level for a large set of possible f and s combinations. This is what we present in Figure 12. If the economy recovers very fast with historically favorable realizations of f and s, it is feasible to reach 4.1 percent within a month, as the lower right corner of Figure 12 indicates. Needless to say, we do not think this is a likely scenario. In fact, anything that falls within the range of f and s combinations that we have experienced during the most recent expansion rules out reaching the level of 4.1 percent within a quarter. However, it seems likely the labor market recovery could be relatively rapid if we experience flow rates in the range of the 2019 average. In that case, the unemployment rate is projected to reach 4.1 percent within two quarters. Note that the upper envelope of the shaded areas in Figure 12 indicates the frontier for the feasible set. Any combination of flow rates, f and s, that lie north of that line will lead the unemployment rate to converge to a level higher than 4.1 percent.

Another way to address the speed of the recovery is to use the evolution of unemployment flows in the earlier recoveries as a benchmark in Figure 13. These simulations assume that the inflow/outflow dynamics follow the earlier recoveries: the 1980s, 1990-91, 2001, and 2007-09 recessions. The left panel of Figure 13 shows that the decline in the unemployment rate after the COVID-19 recession peak was faster than in earlier recoveries as a consequence of the opening of the economy and unprecedented policy measures. The right panel projects the path of the unemployment rate into 2023 under different counterfactual recovery patterns. In all cases, the unemployment rate would be lower than 5 percent by the end of 2021—even following the pattern of the jobless recovery after the 2001 recession. The most drastic decline is embodied in the 1980s recovery, which would bring the unemployment rate to the mid threes by the end of 2021. The Great Recession's dynamics imply something in between, with an unemployment rate of 4.5 percent by the end of the year. According to these projections, the unemployment rate would be between 3.5 to 4.5 percent by the end of 2022.

All of the empirical exercises we depicted in Figures (2) through (13) confirm that despite the significant adverse effects from the pandemic, the US unemployment rate was not poised



(a) First six months

(b) Beyond six months

Figure 13: Unemployment rate projections under alternative recovery patterns for the first six months following the peak unemployment rate and beyond six months

to reach levels last seen during the Great Depression. Moreover, any return to a functional labor market would bring the unemployment rate down relatively quickly.

5 Conclusion

The recession triggered by the COVID-19 pandemic has been devastating for the US labor market. In this paper, we present a flow-based empirical approach to characterize the evolution of the unemployment rate during this episode. In particular, we analyze fluctuations in the unemployment rate through the lens of labor market flows. We show that using labor market flows was helpful to evaluate the extent of the initial spike in the unemployment rate in April and demonstrate why it was unlikely that the unemployment rate would reach more than 20 percent in spite of massive job losses in the spring of 2020. Moreover, unemployment dynamics suggested that despite the unprecedented nature of the shock, the unemployment rate was likely to come down relatively quickly – as it did in the second half of 2020.

Our methodology provides a simple way to use real-time in conjunction with labor market flows to provide projections for the unemployment rate. Current estimates, complemented with scenario analysis, indicate that the unemployment rate will likely end 2021 at 5.4 percent. This is, to a large extent, independent of the potential adverse effects from another round of state-level restrictions on businesses and individuals to curb the pandemic. The temporary effects from these restrictions might be substantial, yet transitory.

Even though the unemployment rate is one of the best summary measures of the health of the labor market, there are other important measures to fully evaluate the adverse effects on the labor market. For instance, labor force participation dropped more than 3 percentage points in the first two months of the pandemic and has not recovered to the extent that the unemployment rate did. School-closure-induced child care demands and fear of getting infected in the workplace might have played an important role in the subdued recovery of the participation rate down. A full recovery on the participation margin might take much longer. We abstract from these important issues in this paper and leave it for future research.

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