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Nowcasting Unemployment Insurance Claims in the Time of COVID-19

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Keywords

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JEL Classification

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Abstract

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1 Introduction

Simple time series models often forecast well in normal times (see the long literature started by Nelson (1972)), but in the midst of dramatic upheaval, such as in the first few weeks of the response to COVID-19, these models do not adjust quickly to changing conditions (Castle, Clements, and Hendry (2016)). These models exploit a long time series of an aggregate to estimate precise, consistent estimates, while typically ignoring information on disaggregate components. We argue that in times of structural change, forecasters should attempt to exploit information within disaggregates, especially when there exists timing variation in the breaks among the disaggregate entities. In the case of the spring of 2020, we find variation in state-level COVID-19-related state-of-emergency declarations provides useful information for predicting the national quantity of initial unemployment insurance claims.

The number of persons filing initial claims for unemployment insurance (UI) is an important indicator of current US economic conditions (Berge and Jordà, 2011; Lewis, Mertens, and Stock, 2020). UI data is both timely and frequent, and is one of a limited number of macroeconomic indicators available at a weekly cadence. As the COVID-19 pandemic came to the US, it became an important indicator used to evaluate the state of the economy and the economic toll of the pandemic and associated stay-at-home orders in near-real-time. It also became itself a key variable to forecast, in part as an input to estimates of monthly unemployment rate forecasts.[1]

In this paper we present current week forecasts (i.e. nowcasts) of the advance estimates of US national initial unemployment claims produced with different information sets and data structures.[2] We show that a small T panel model performs well shortly after a structural break if it has relevant information. The variation in emergency declaration date across the states provides this relevant information and outperforms models including Google Trends data as well as autoregressive models. We further show that autoregressive models do catch up within a few periods, but that they perform poorly in the crucial weeks directly after the dramatic increase in claims that came in mid-March of 2020.

Other researchers have recognized the need for different tools to forecast UI claims in the time

[1] The insured unemployed in the US is a subset of all unemployed since many jobless do not qualify or apply for benefits.

[2] Wright (2019) emphasizes the important role of nowcasts in macroeconomic forecasting.

of COVID-19 beyond simple time series models. Aaronson, Brave, Butters, Sacks, and Seo (2020) use an event-study approach based on hurricanes in order to use Google Trends data to forecast claims. Goldsmith-Pinkham and Sojourner (2020) also use Google Trends at the state level to forecast claims. Our innovation is to use the timing of emergency declarations across the states in a panel framework. We compare our forecasts to those produced using Google Trends in both panel and time series frameworks as well as with autoregressive models. We show that all models miss the initial shock, but that in the early periods the information in the declaration weeks panel leads to substantially better forecasts. Quickly thereafter, the time series models catch up. Google Trends models are typically second- or third-best in each time period, outperforming autoregressive models initially, but still underperforming declarations dummy variable models.[3]

Our research also connects to the debate about forecasting the aggregate or aggregating forecasts (see discussion in Castle and Hendry (2010), Hendry and Hubrich (2011), Larson (2015), and Heinisch and Scheufele (2018)). We find support for forecasting the individual states and then aggregating in the case when we have variation in the timing of the states that is useful, e.g. the emergency declaration dates, which is consistent with the argument from Castle, Fawcett, and Hendry (2011) that we need relevant information available to forecast during breaks. After the usefulness of that information is exhausted, however, simple autoregressive models perform best with little difference between direct national forecasts and aggregates of state forecasts.

Research using Big Data for forecasting has emphasized the importance of a large number of time observations for forecasting but in the face of structural breaks we may not have a long time series with consistent parameters (Bajari, Chernozhukov, Hortaçsu, and Suzuki, 2019). We may, however, have useful information in the panel dimension. Since we have variation in the timing of the emergency declaration by state we can exploit this information using dummy variables in a panel framework. We show that in this case the cross sectional information does improve forecasts in the periods near the structural break.

The remainder of our paper is as follows. First, we describe the UI claims, Google Trends, and disaster declaration series. Next, we describe the models used to generate pseudo real-

[3] Google Trends have been shown useful in other contexts, including forecasting the US unemployment rate (D'Amuri and Marcucci, 2017) and nowcasting GDP, particularly when official data are not available (Ferrara and Simoni, 2019).

time forecasts, paying particular attention to information set assumptions regarding variables and timing and the structure of the data. Then, we turn to a discussion of our results, after which we conclude. Detailed model estimates and alternative forecasts can be found in the appendix.

2 Data

2.1 Unemployment insurance claims

Our target variable is the national total of the advance number of initial unemployment insurance (UI) weekly claims under state programs, not seasonally adjusted (NSA). Figure 1, panel *a* reports this variable for each week since January 1998. The previous peak, near the end of the Great Recession, was just under 1 million people filing initial UI claims. In early 2020, the US economy was relatively strong, with around 215,000 weekly claims each week in February. In response to the COVID-19 pandemic and stay-at-home orders, claims quickly dwarfed the Great Recession high, rising almost 30-fold from this benchmark entry, with claims exceeded 6 million in a single week (panel *b*). Our analysis is focused on this crisis period and our forecasts begin for the week of March 14, 2020. Our objective throughout the paper is to forecast the advance release of the series presented in Figure 1.

Initial unemployment insurance claims are released each Thursday morning at 8:30 am Eastern Time by the US Department of Labor (DOL) and the latest data are the preliminary estimates for the week ending the Saturday five days prior. Each week our dataset contains initial claims by state for a total of 52 entities in the panel: 50 US states plus the District of Columbia (DC) and Puerto Rico.[4] We refer to all the entities as states for simplicity. The objective of the forecasts will be the advance national totals which are directly calculated as a sum of the 52 state entities.[5] We focus on not seasonally adjusted (NSA) numbers throughout our analysis, following the recommendation of Rinz (2020), since the multiplicative seasonal adjustment procedure that is used for UI claims is likely misleading in the case

[4]We do not model the US Virgin Islands, which typically has fewer than 100 claims per week.

[5]We are focused on the initial claims under state programs, not the additional claims for the national Pandemic Unemployment Assistance from the CARES Act (info at `https://www.dol.gov/coronavirus/unemployment-insurance`.

of the magnitudes of changes in the sample we are analyzing.[6] Our pseudo real-time dataset is constructed using the historical weekly file available on the DOL website through the week ending March 7th, 2020, and then press release PDF files.[7]

All models are estimated on data available at the time the forecast was made. In our exercise, forecasts are assumed to be made immediately following the Thursday release for the next week's release. Unemployment claims data are generally revised once, meaning that the last observation used in each week's estimates will be preliminary data ("advance" estimates in the Department of Labor terminology) that is updated the following week.[8]

In our analysis, we develop several forecasting models which exploit different samples of data and variable transformations. For autoregressive models (both state and national), our dependent variable is the natural log of weekly UI claims, and our sample begins in January 1998 in order to exploit a large number of periods, satisfy "Large T" asymptotics, and ensure ergodicity. Augmented Dickey-Fuller tests confirm this series to be stationary despite the rising labor force over the period, with all tests rejecting the null of non-stationarity at the 1% level.

In models exploiting the panel dimension–"Large N" models–our dependent variable is normalized weekly US claims for each state relative to the last pre-crisis week, which we identified to be the second week of February (the week ending February 15). Thus, for each state the normalized data = 1 for the week ending February 15th. We then reverse this normalization

[6] The use of seasonally adjusted (SA) versus not seasonally adjusted (NSA) numbers has been the subject of some debate in the COVID-19 downturn. Seasonal adjustments to advance weekly UI claims are multiplicative, which we believe to be overestimates of the true seasonal effect. Accordingly, we use NSA numbers throughout the paper. For some context, the seasonal adjustment to the week ending March 28th was over 600,000 (6.4m SA vs 5.8m NSA). The prior year's UI claims numbers for the same period were, respectively, 211,000 and 180,000, giving a seasonal effect of 31,000. See `https://www.dol.gov/sites/dolgov/files/OPA/newsreleases/ui-claims/20200551.pdf` for the May 2nd, 2020 press release (accessed 5/28/2020). This file has been downloaded and retained by the authors and is available upon request.

[7] These files are available at `https://oui.doleta.gov/unemploy/DataDownloads.asp` series ETA 539 and `https://oui.doleta.gov/unemploy/archive.asp`, respectively.

[8] For our real time dataset we assume the data are revised only once, so each week we update our dataset with the "advance" estimates for the previous week along with revised estimates for the week before that. There was one clear data error where preliminary data for Connecticut for the week ending on May 9th was originally reported as 298,680, but was quickly corrected to 30,000 per the Wall Street Journal: `https://www.wsj.com/articles/unemployment-claims-keep-piling-up-in-tri-state-area-11589471382`. We have used the corrected number as the preliminary value for Connecticut in this case and adjusted the national values appropriately.

when we aggregate back to the national level to produce the forecast of US national NSA initial unemployment claims. Our panel sample period begins the week ending February 1st, week 5 of 2020.

2.2 Emergency declaration dates

Our declaration date analysis is based on the week in which a state of emergency was declared regarding COVID-19 for that state. All states as well as DC and Puerto Rico declared a state of emergency within a four week period in February and March of 2020 (Table 1). Washington State was the first to declare an emergency on February 29th and West Virginia was the last on March 16th. Figure 2, panels *a* through *d*, show normalized state claims grouped by their week of declaration where 0 on the x-axis for each group is the week that group declared their emergency. From these figures it is clear that all states experienced a substantial increase in claims after declaring a state of emergency. The last states to declare an emergency already had increases before their declaration week, but continued to experience further increases in the weeks following.

2.3 Google Trends

The Google Trends data is an index of the relative search volume on Google for the keyword "unemployment" for the US and for each of the 50 states plus DC and Puerto Rico.[9] The Google Trends API only allows five comparison locations per search, so, following Goldsmith-Pinkham and Sojourner (2020), we include California in each of our rounds of data collection and re-normalize each state relative to California. This approach allows us to compare across time and states. In order to get a long daily time series for the national trend we follow a similar approach pulling each six month time period along with the initial six months.

It is important to note that the models including Google Trends are true nowcasts in the sense that they are using information available into the target week. Google Trends data is available with an approximately 36 hour delay, so for forecasts made on Thursday morning for the data that will be released the following week, we already have Google Trends data through Monday of the reference week. In order to use all information available at the time of our forecast, we create two different Google Trends variables. We include the average of the previous week, where the dates line up with the latest available UI claims numbers,

[9] Aaronson, Brave, Butters, Sacks, and Seo (2020) also use the keyword "unemployment." We also considered "file for unemployment" following Goldsmith-Pinkham and Sojourner (2020) with little impact on the results. One interesting finding is that including both keywords helps the national forecast and seems to be a good way to manage sampling error, but we leave deeper exploration of this issue to further research.

which we call G_{t-1}. We also include a separate variable that is the average of the two days that are available in the current week, which we call $\tilde{G}_t$.[10]

Similar to the UI claims, the Google Trends are normalized by their average value from the week ending February 15. Since there are many cases of zeros in Google Trends, we first add 1 to all values, and then the Trends are divided by the average of 2/9 through 2/15 in the case of G and by the average value of 2/9 and 2/10 in the case of $\tilde{G}$.

Google Trends data are available from January of 2014. We use the full series for the national time series model. For the panel models we start in February of 2020.

3 Models

Our forecast target is weekly US national initial unemployment claims with a focus on the first release, which is announced the Thursday of the week following the reference week. The nomenclature for the horizon of our forecast is tricky. Models that do not include Google Trends or disaster emergency declaration data can plausibly be considered one-week-ahead forecasts since they are based on data through the previous week. However, the UI claims data on the previous week is only released on Thursday morning of the current week, which means we cannot produce the forecasts until well into the current week. Thus if we name the horizon based on when we are able to make the forecast, it would be a current-week forecast, aka a nowcast. We estimate each of our models with data available on Thursday morning of the reference week, thus the Google Trends data is available through Monday of that week, and declarations for the current week made after Wednesday are assumed not to have been made at the time of the forecast. Following Banbura, Giannone, Modugno, and Reichlin (2013), we will use the term nowcasts for all models.

We consider several combinations of data structures and information sets. Data structures considered include US state level panel models, state time series models that do not exploit the panel dimension, and national time series models that do not exploit any disaggregate information. For the state level data we sum up to the national level for evaluation of the forecast. For information sets we use single-series autoregressive models, Google Trends at the state and national level, depending on the model, and dummy variables based on the

[10]We also considered a single variable of the latest 7 days available, but it performed worse in our forecasting models.

week of the emergency declaration by state. In the main results section we report a total of 6 different models, where in the case of state level models we aggregate back to the US national values for the final forecast, which we describe below in greater detail.

Our main model is a panel model with dummy variables representing the distance week t is from state i's emergency declaration date. The variation in this information is what gives our panel good forecasting properties.[11] The panel regression is weighted based on covered employment for each state for the week ending March 7th.

In this model, state differentials in declarations timing gives us information about future UI claims behavior. The states are in 4 different groups based on the timing of their emergency declaration. Washington State was the first to declare an emergency on February 29th, which we classify as a "Week 1" declaration. The remaining states all followed suit over the next three weeks (see Table 1) and are given labels of Weeks 2 through 4. Our first nowcast was made on March 12th for the week ending March 14th.

The timing of our nowcasting exercise affects the availability of information on declaration dates. To illustrate, for the nowcast for the week ending March 14th, we use all information available up to March 12th, which includes the UI claims release that morning covering the week ending March 7th, and all declarations up to March 11th. All Week 1 and Week 2 declaration states have dummies set equal to 1 in their respective week. However, for Week 3 states, only about half of the states would have dummy variables set equal to 1 for the week ending March 14th in this particular forecast vintage, because declarations after March 11th are not included. All other Week 3 and Week 4 declaration states have dummy variable set equal to 0 in all periods in this vintage. For the March 21st forecast vintage, the remaining Week 3 states would have their dummy variables set equal to 1 for the week ending March 14th, and so on.

In terms of notation, j is how many weeks state i is away from emergency declaration at time t. So, for instance, in the week ending March 14th, the dummy variable, d_{ijt} for Washington, whose declaration date is February 29th is 1 for $j = 2$ and 0 otherwise. By the same logic, the dummy variable in the same time period for California (declaration date of March 4th)

[11] Once we know the dates of all the emergency declarations, this model is equivalent to a panel structured around the week each state declared an emergency, but we keep it structured around calendar time to ease aggregation and forecasting.

is 1 for $j = 1$ and 0 otherwise. We also include dummy variables for the two periods in advance of the declaration once the declaration date is known. Thus we estimate $J + 3$ dummy variables, where J is the number of weeks since the week ending February 29th: two leads, one concurrent to the declaration date, and J lags.

$$NormStateClaims_{it} = \beta_0 + \sum_{j=-2}^{J} \beta_{j+3} \times d_{ijt} + u_{it} \tag{1}$$

We also estimate panel models including Google Trends data for each state, where G_{it-1} for total of the full week before and $\tilde{G}_{it}$ for the total of the Monday and Tuesday of the current week.[12]

$$NormStateClaims_{it} = \beta_0 + \beta_1 G_{it-1} + \beta_2 \tilde{G}_{it} + u_{it} \tag{2}$$

Normalized state claims are aggregated to national claims in several steps. First, we undo the normalization by multiplying estimated normalized claims by the February 15 value of state claims. Next, we aggregate to the national level by summing the 52 state estimates. Finally, because the estimator for the normalized data is not unbiased in terms of the national sum, we include a bias adjustment term b that is equal to the percent error from the last in-sample predicted value. This is akin to intercept correcting a forecast based on the last estimated error.[13]

$$U\widehat{SClaim}s_t = \hat{b}_t \times \sum Norm\widehat{StateC}laims_{it} \times StateClaims_{i,Feb15}$$

where

$$\hat{b}_t = USClaims_{t-1} / \left(\sum Norm\widehat{StateC}laims_{it-1} \times StateClaims_{i,Feb15} \right)$$

[12] A model with both declaration week dummy variables and Google Trends performed similarly to a model with just declaration week dummy variables. The results for this model are reported in Table A.5 in the appendix.

[13] For discussion of aggregation bias, see Goodfriend (1992), Pesaran and Smith (1995) and Baltagi (2008). Our approach is similar to a forecast error intercept correction, except that instead of taking the forecast error from the model used the previous period, we re-estimate the model this period and use the in sample residual for the last observation, which was the forecast target last period.

The variable $\hat{b}_t$ consists of lagged values in the data, but is only available once the information set at time t is available.

The panel models are then compared to state and national time series models. For state level autoregressive models, we model the natural log of the state claims separately for each state i:[14]

$$ln(StateClaims_{it}) = \beta_{i0} + \sum_{j=1}^{p} \phi_{ij} \ln(StateClaims_{it-j}) + u_{it} \tag{3}$$

We aggregate the state claims to the national level, first by exponentiating and adjusting for the variance of the residuals to correct for bias from Jensen's inequality

$$\widehat{StateClaims}_{it} = \exp\left(\ln(\widehat{StateClaims}_{it}) + 1/2 \times \hat{\sigma}_u^2\right)$$

and then summing across the 52 states.

The national level model with Google Trends is as follows, where normalized US claims is the modeled variable. When calculating the estimated US claims value, we use the same aggregation bias correction method as the state model but with national claims instead of state claims.[15]

$$NormUSClaims_t = \beta_0 + \beta_1 G_{t-1} + \beta_2 \tilde{G}_t + u_t \tag{4}$$

The national level autoregressive model of order p is estimated in the same way as the states, with the level value calculated using the estimated residual variance to adjust for Jensen's inequality.

$$ln(USClaims_t) = \beta_0 + \sum_{j=1}^{p} \phi_j \ln(USClaims_{t-j}) + u_t \tag{5}$$

[14] We also estimated a state level AR model with declaration week dummy variables, but the results were little different than the model without them.

[15] We also estimated a model with Google Trends and AR terms. This model slightly outperforms the model without AR terms. We report forecasts from this model in the appendix.

4 Results

We report forecasts for 10 weeks from the week ending on March 14th, 2020, through the week ending May 16th, 2020. The forecasts are depicted in Figure 3 along with the actual values of the advance data for the national UI claims which is the target of the forecasts. Forecast percentage errors and associated statistics are available in Table 2. The models reported line up with the equations in the previous section. Models 1 through 3 use state level data while models 4 and 5 use national level data. Models 1 and 2 use a panel data structure, with our main focus being the panel declaration dummy variable ("declarations DV") model. The remaining models use a time series data structure. For the autoregressive models, both state and national, we report results using with $p = 3$. We include Google Trends in the panel framework for Model 2 and in the national time series framework for Model 4.

Focusing on the beginning of the sample, all models perform poorly in the first two weeks. The popular narrative surrounding UI claims highlights the spike for the week ending March 21st, when national claims jumped to a historic high of nearly three million from the previous week of just over 250,000. However, there was also a spike in the week ending March 14th, when claims rose from around 200,000 to 250,000. We can see from Table 2 that in the first week all models miss by double-digit percentage points and in the second week the forecast errors rise to 80-90%. In these two periods, no model forecasts substantially better or worse than any other.

In the third week of our forecast analysis, the week ending March 28th, all models miss again, but the declarations DV forecast misses by far less than other models, with a percentage error of -27%. The national Google Trends forecast is second-best, with an error of -37%. No other forecast has an absolute error less than 50%.

The information contained in the declaration week dummy variables was fully populated in this period, with every state having declared a state of emergency by the time of the forecast. The experiences of Washington, California, New York, and some of the earliest-hit states were predictive of patterns exhibited in other states. The timing differentials were key in forecasting variation in UI claims in states with later declarations.[16]

Table 3 presents our parameter estimates for each vintage week for the state declaration models. We add an additional parameter each week as we move one week further away from the first emergency declaration. Parameter estimates improve from week to week as we get more variation from additional states. For example if we look at the estimated parameter on the dummy variable when $j = 2$ we can follow across the row to see how the parameter varies as we get more information from more of the states. For the model estimated with data through March 12th for the week ending March 14th, there is only one observation that has a one for this variable, Washington in the latest period. Then the following week the states in the week 2 group have a one for this variable in the last week, and Washington in the week before, so we get a more precise estimate, and so on for two more weeks until we get as much information as we can get from the states after 4 weeks. Then the 5th week we still have data revisions that affect the parameter estimates, but it is stable after that. A similar pattern appears for all the coefficients on the dummy variables.

In the fourth week, the declarations DV model reaches its peak in terms of benefit relative to other models. The forecast misses by only 4%, where no other model has an error less than 22%. In sum, in weeks three and four, the information from the emergency declarations results in forecast improvements relative to the models without emergency declarations.

This period is crucial because the week ending April 4th was the week of peak claims over this period (and up to this point in the history of the series) with over 6.2 million people filing initial unemployment claims across the country. The percentage forecast error does not fully capture the absolute forecast error in these periods; absolute forecast errors for this period are about 200,000 for the declarations DV model compared to 1,000,000 to 3,000,000 for the alternative models. In the latter case, these errors far exceeding the previous high in actual claims before COVID-19 of about 1,000,000 (see the appendix).

In the weeks ending in April 11th and 18th, the relative strength of the forecasting approaches becomes less clear and it is debatable which forecasting approach is preferred. The trend in the forecast errors for the panel models is clearly pointing to plateauing performance, with

[16] We estimated several other variants of the models reported, such as including Google Trends in the AR models and panel AR(1) models with Google Trends and state declarations, but they typically performed worse than the models reported (see the appendix).

both each have average absolute forecast errors of around 10% in these weeks. The state and national AR models, on the other hand, have similar forecast errors but they are showing monotonic improvements in forecasting performance since March 21st. The national Google Trends model continues to forecast poorly.

In the week ending April 25th through the end of the sample on May 16th, the AR models are clearly superior, thought the percent errors are generally smaller across all models and the absolute number of claims is also smaller. Consequently, the cost of choosing an inferior forecast in this period is much lower than in the earlier periods. Absolute forecast errors hover between 1% and 6% while the panel models continue to average around 10% to 15%. This corresponds to absolute error differences between the two forecasting approaches of about 100,000 to 200,000.

The information gained by exploiting the panel dimension is offset by the inefficiency of estimating individual dummy variable coefficients. Figure 5 illustrates this phenomenon at a state-level. In the April 4th vintage, the actual values are almost uniformly above the State AR model forecasts. By the May 16th vintage,the bias is mostly gone and is no longer significant. The Declarations DV model, on the other hand, is not significantly biased in either period, but it has a larger variance around the actual values, particularly for the week ending May 16th. When we observe these vintage coefficients from the declarations DV models in Table 3, we can see the clear trend in the parameters when look at descending rows within each column. In the final period model, the coefficients trace out a hump-shaped curve with a tail that is decreasing at a decreasing rate. This is an inefficient way of modeling what is essentially the same type of decay found in an AR model. Consequently, AR models outperform the panel DV model at the end of the sample.

Based on our analysis we can divide our sample into four distinct periods: (1) the first two periods when the crisis is ramping up and all models perform poorly; (2) the next periods when panel model with declaration DVs stands out; (3) a period of ambiguity where models begin to converge; and (4) and at the end when the AR models stand out as best. Not all periods are equal, however. In the periods immediately following the onset of the COVID-19 outbreak, both the level of the claims and the percent errors are larger. Accordingly, over the full sample, the Harvey, Leybourne, and Newbold ("HLN") (Harvey, Leybourne, and Newbold (1997))-adjusted Diebold Mariano, "DM") test Diebold and Mariano (2002) rejects equal predictive accuracy in favor of the declaration dates panel model when comparing with any of the Google Trends models (equations 2, 3, and 6). The AR models also perform worse over the full sample, but not statistically significantly so.

5 Conclusion

In this paper we produced current week forecasts (aka nowcasts) for the national total of state initial unemployment insurance (UI) claims for ten weeks in the midst of the COVID-19 pandemic in the US. We considered different data structures and information sets and compared their performance. We found that in the weeks immediately following the jump in UI claims associated with the COVID-19 crisis that a panel model exploiting the time variation in states declaring a state of emergency performed remarkably well with the lowest mean absolute error for the full sample across the competing models and statistically significantly better than models including Google Trends data that was available at the time the forecasts were made. Autoregressive models caught up in a few weeks and in the last weeks of the sample had the smallest absolute errors.

Prior research has emphasized the usefulness of simple autoregressive models in normal times, but has recommended much more complicated models for recessions in order to incorporate sufficient relevant information to identify the change in regime (Chauvet and Potter, 2013). Our findings support the view that simple autoregressive models miss dramatic changes, but we show that it is possible in certain instances to exploit panel information if there is information on differences in timing in the cross section.[17] This allows us to still use a simple model for forecasting in the time of structural change. Our analysis also emphasizes that autoregressive models are still remarkably useful just a few periods after a break.

[17] The use of spatial timing differentials to identify and predict effects is common in the urban and regional economics literature. See, for instance, the literature which uses Wal-Mart store and distribution center diffusion from Arkansas for identification (Neumark, Zhang, and Ciccarella, 2008).

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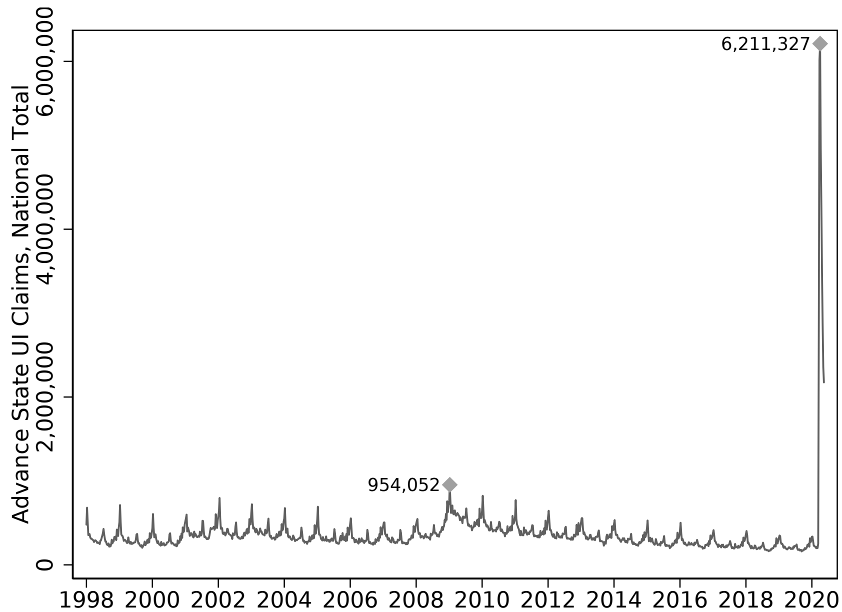
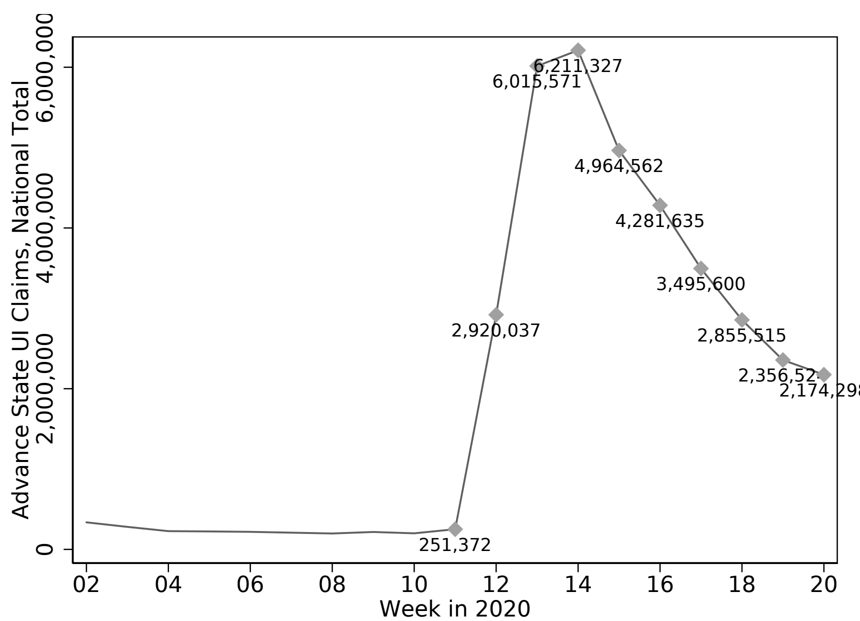
Figure 1: National UI Claims

(a) January 1998 - May 2020



(b) January 2020 - May 2020

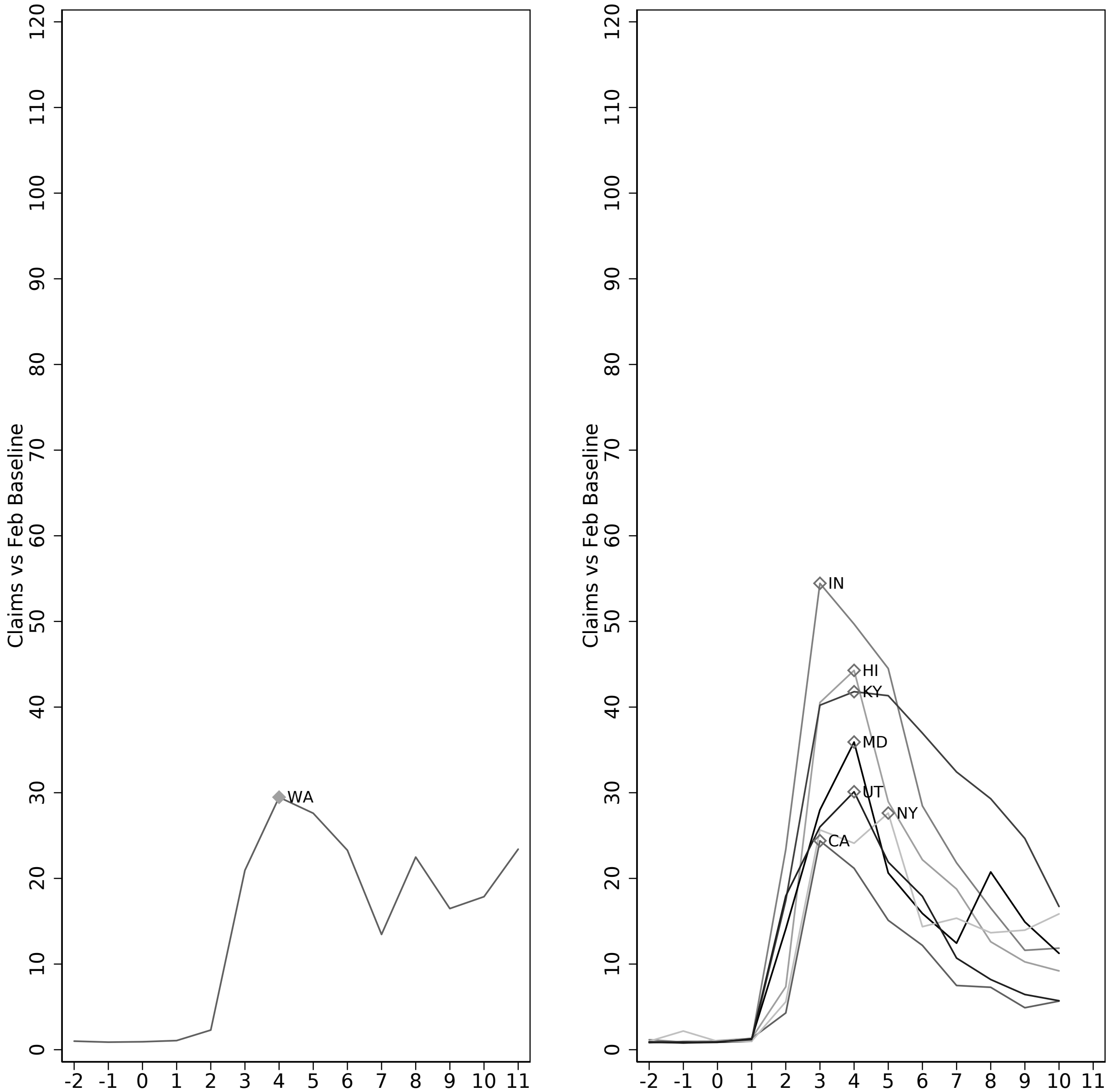


Notes: Data present the advance estimate of U.S. total (50 states plus District of Columbia and Puerto Rico) weekly initial unemployment insurance claims.

Figure 2: State UI Claims

(a) Week 1 Declaration States
(0 = week ending February 29, 2020)

(b) Week 2 Declaration States
(0 = week ending March 7, 2020)

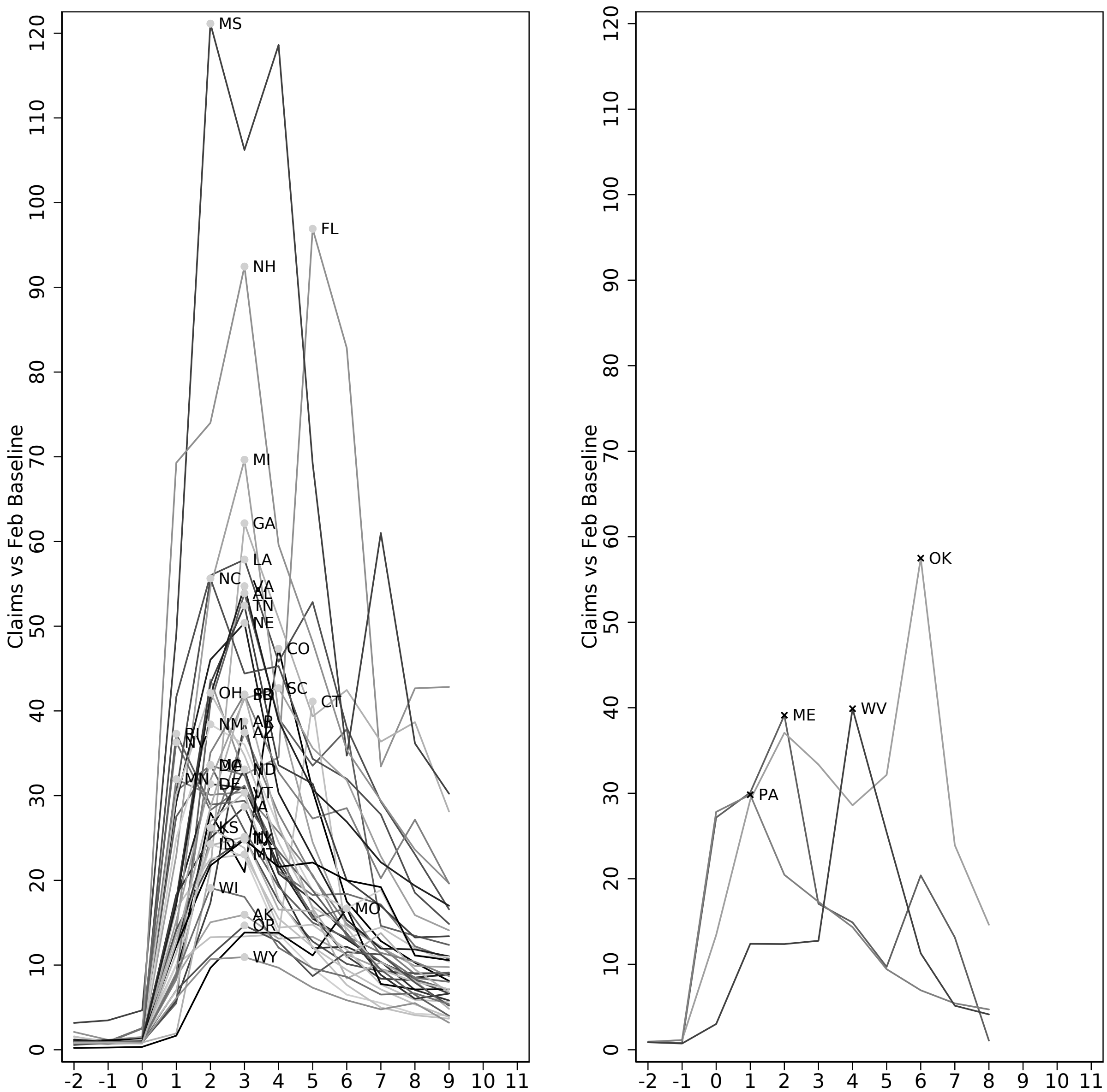


Notes: Data present UI claims normalized with respect to the week ending February 15, 2020 in the respective state. Time is normalized such that 0 is the week of the initial COVID-19 emergency declaration.

Figure 2: State UI Claims, Continued

(c) Week 3 Declaration States
(0 = week ending March 14, 2020)

(d) Week 4 Declaration States
(0 = week ending March 21, 2020)



Notes: Data present UI claims normalized with respect to the week ending February 15, 2020 in the respective state. Time is normalized such that 0 is the week of the initial COVID-19 emergency declaration.

Figure 3: Alternative Forecasts of Weekly UI Claims

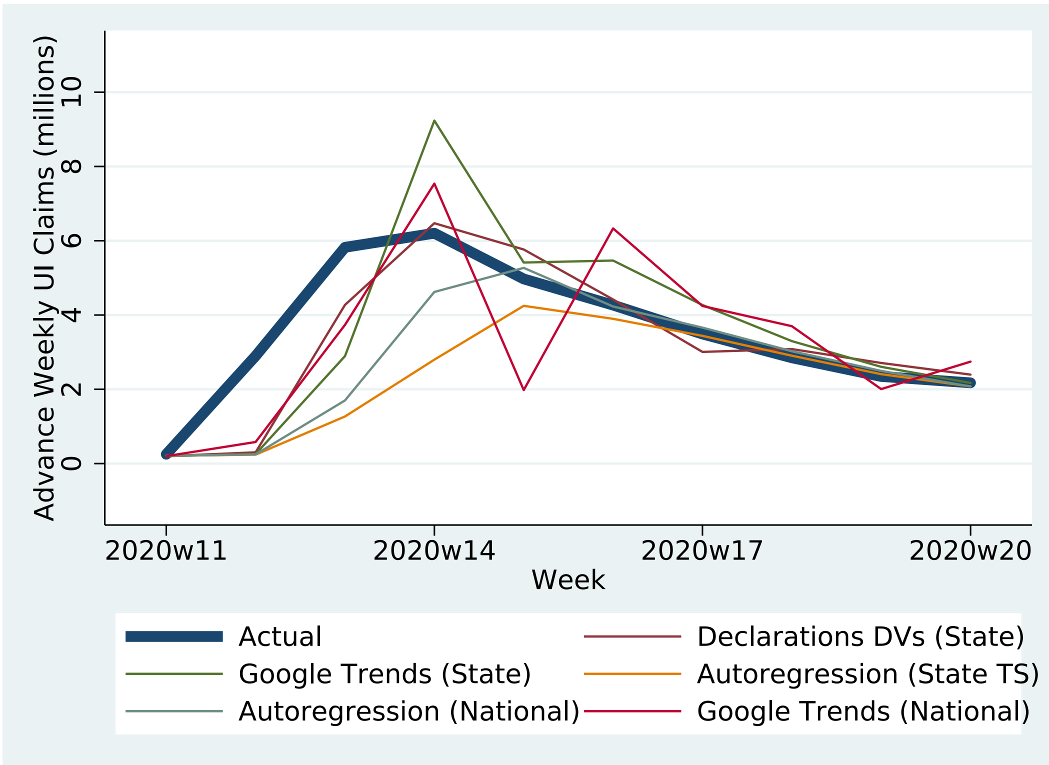
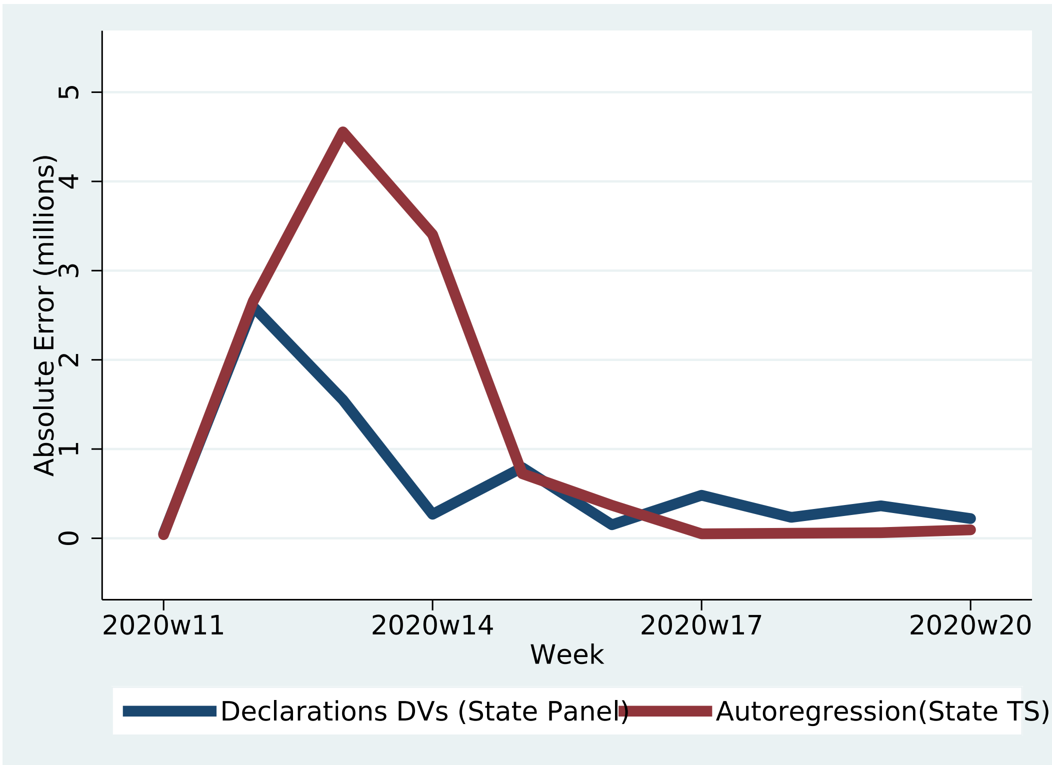


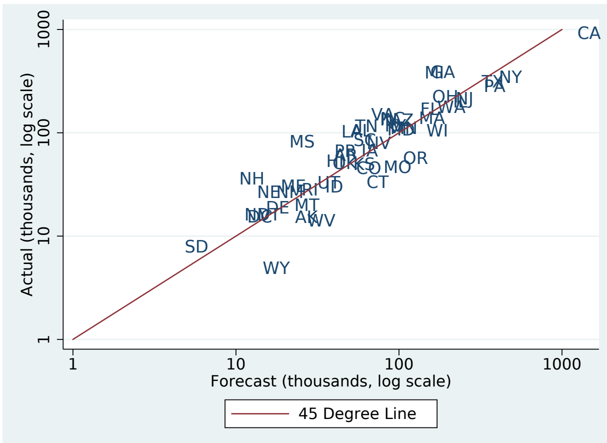
Figure 4: State Panel Declarations DV versus State AR Models



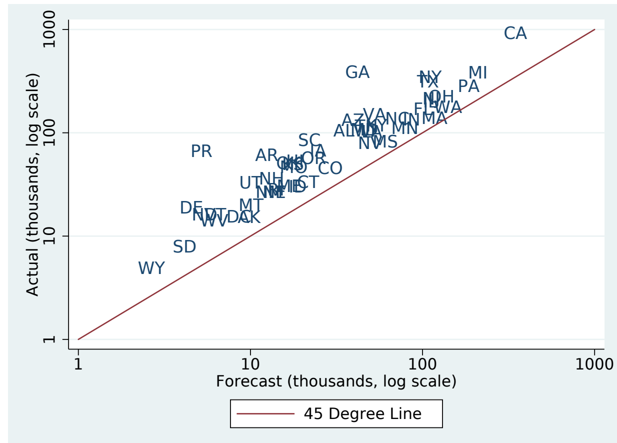
Notes: This figure presents the MAE for two forecasts: [1] ("Declarations") and [3] ("State AR") from Table 2. The figure shows MAE nearly equal in the first week (Week 11). In weeks 2 and 3, the Panel Declarations DV forecast substantially outperforms the State AR forecast. In weeks 4 and 5, both perform similarly. After week 5, the State AR forecast is consistently more accurate than the Declarations forecast.

Figure 5: State-Level Forecasts, Declarations DVs vs State AR

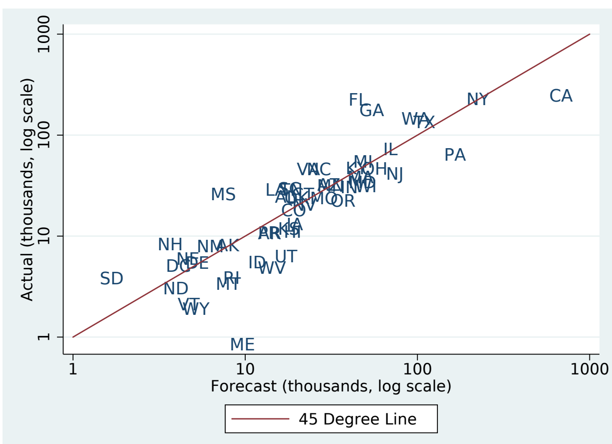
(a) Declarations DV, week ending April 4th
$\hat{\alpha} = 0.04(0.07)$, $SER = 0.49$



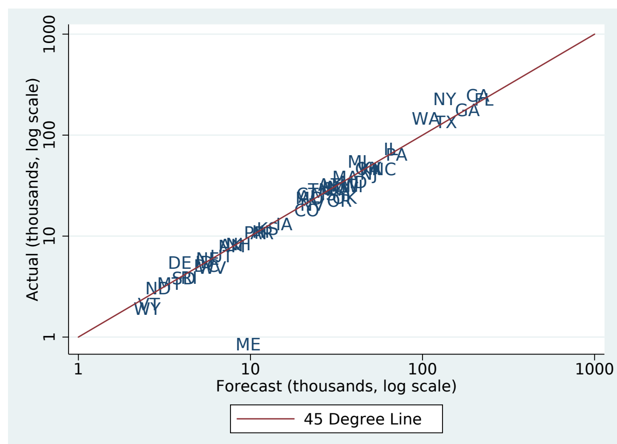
(b) State AR, week ending April 4th
$\hat{\alpha} = 0.84(0.06)$, $SER = 0.44$



(c) Declarations DV, week ending May 16th
$\hat{\alpha} = 0.09(0.10)$, $SER = 0.69$



(d) State AR, week ending May 16th
$\hat{\alpha} = -0.07(0.05)$, $SER = 0.37$



Notes: Data present actual and forecast UI claims by state in two weeks: the week ending April 4th and the week ending May 16th. The Declarations DV forecasts are aggregation-bias corrected. Estimated parameters (and standard errors in parentheses) are from the following Holden and Peel (1990) models estimated across states i within a particular week, where f is the forecast in the figure panel:
$\ln(StateClaims_i) - ln(f_i) = \alpha + u_i$.

Table 1: COVID-19 Disaster Declaration Dates

Week 1		**Week 3, Continued**	
Washington	2/29/2020	Kansas	3/12/2020
Week 2		Montana	3/12/2020
California	3/4/2020	Nevada	3/12/2020
Hawaii	3/4/2020	Puerto Rico	3/12/2020
Maryland	3/5/2020	Tennessee	3/12/2020
Indiana	3/6/2020	Virginia	3/12/2020
Kentucky	3/6/2020	Wisconsin	3/12/2020
Utah	3/6/2020	Alabama	3/13/2020
New York	3/7/2020	Arkansas	3/13/2020
Week 3		Idaho	3/13/2020
Oregon	3/8/2020	Minnesota	3/13/2020
Florida	3/9/2020	Missouri	3/13/2020
Illinois	3/9/2020	Nebraska	3/13/2020
Iowa	3/9/2020	New Hampshire	3/13/2020
New Jersey	3/9/2020	North Dakota	3/13/2020
Ohio	3/9/2020	South Carolina	3/13/2020
Rhode Island	3/9/2020	South Dakota	3/13/2020
Colorado	3/10/2020	Texas	3/13/2020
Connecticut	3/10/2020	Vermont	3/13/2020
Massachusetts	3/10/2020	Wyoming	3/13/2020
Michigan	3/10/2020	Georgia	3/14/2020
North Carolina	3/10/2020	Mississippi	3/14/2020
Alaska	3/11/2020	**Week 4**	
Arizona	3/11/2020	Maine	3/15/2020
District of Columbia	3/11/2020	Oklahoma	3/15/2020
Louisiana	3/11/2020	Pennsylvania	3/16/2020
New Mexico	3/11/2020	West Virginia	3/16/2020
Delaware	3/12/2020		

Source: Authors' assembly based on publicly available news reports.

Table 2: Forecasting Results

Data Structure:		State - Panel	State - Panel	State - Time Series	National	National	
Information Set:		Declaration DVs	Google Trends	Autoregression	Google Trends	Autoregression	
Week Ending	U.S. Claims	[1]	[2]	[3]	[4]	[5]	Average
3/14/2020	250,869	-20%	-20%	-16%	-20%	-16%	-19%
3/21/2020	2,898,392	-90%	-91%	-92%	-80%	-91%	-89%
3/28/2020	5,823,757	-27%	-50%	-78%	-36%	-71%	-52%
4/4/2020	6,203,348	4%	49%	-55%	22%	-25%	-1%
4/11/2020	4,971,820	16%	9%	-15%	-60%	6%	-9%
4/18/2020	4,267,394	4%	28%	-9%	48%	-1%	14%
4/25/2020	3,489,173	-14%	22%	-1%	22%	5%	7%
5/2/2020	2,849,079	8%	16%	2%	30%	6%	12%
5/9/2020	2,345,376	16%	11%	3%	-14%	6%	4%
5/16/2020	2,174,298	10%	0%	-4%	26%	-5%	5%
Mean Error		264,722	-53,914	1,177,818	221,304	773,600	476,706
MAE		671,228	1,178,798	1,201,582	1,336,233	933,113	758,522
RMSE		1,016,818	1,651,462	2,002,284	1,626,767	1,634,753	1,291,707
MAE-DM			-2.832***	-1.676*	-4.240***	-1.247	

Notes: This table presents percentage forecast errors made on the Thursday of the week ending in the date listed in the row. MAE is the mean absolute forecast error. RMSE is the square-root of the mean squared forecast error. MAE-DM is the Diebold-Mariano small-sample test statistic relative to model [1], with ***: $p < 0.01$, **: $p < 0.05$, and *: $p < 0.1$, respectively. All statistics are at the national level, including Mean Error, MAE, RMSE, and MAE-DM, which are calculated over the 10 forecast periods.

Table 3: Model [1] (Declarations DV Model) Vintage Estimates

Dependent variable: Normalized State UI Claims ($StateNormClaims$)

	Model Vintage									
Parameter	3/14/2020	3/21/2020	3/28/2020	4/4/2020	4/11/2020	4/18/2020	4/25/2020	5/2/2020	5/9/2020	5/16/2020
$d_{j=-2}$	-0.153***	-1.430***	-0.0461	-0.0461	-0.0461	-0.0461	-0.0461	-0.0461	-0.0461	-0.0461
$d_{j=-1}$	-0.130***	-1.411***	-0.0552	-0.0552	-0.0552	-0.0552	-0.0552	-0.0552	-0.0552	-0.0552
$d_{j=0}$	-0.0402	-1.228***	1.366*	1.423*	1.423*	1.423*	1.423*	1.423*	1.423*	1.423*
$d_{j=1}$	0.231***	11.88***	14.87***	15.58***	15.59***	15.59***	15.59***	15.59***	15.59***	15.59***
$d_{j=2}$	1.355***	7.141***	27.73***	27.84***	28.40***	28.39***	28.39***	28.39***	28.39***	28.39***
$d_{j=3}$		19.14***	31.26***	34.63***	33.70***	33.78***	33.86***	33.86***	33.86***	33.86***
$d_{j=4}$			29.19***	33.88***	28.64***	28.18***	28.27***	28.34***	28.34***	28.34***
$d_{j=5}$				27.47***	27.57***	24.04***	23.51***	23.87***	23.87***	23.87***
$d_{j=6}$					23.23***	20.42***	19.12***	18.74***	18.83***	19.13***
$d_{j=7}$						13.33***	15.55***	14.24***	14.59***	14.38***
$d_{j=8}$							22.46***	15.49***	12.28***	11.71***
$d_{j=9}$								16.56***	11.89***	10.28***
$d_{j=10}$									17.70***	10.84***
$d_{j=11}$										22.38***
Constant	1.038***	2.380***	1.035***	1.035***	1.035***	1.035***	1.035***	1.035***	1.035***	1.035***
Obs	364	416	468	520	572	624	676	728	780	832
RMSE	0.051	0.222	0.607	0.654	0.614	0.590	0.562	0.556	0.540	0.531
R^2	0.332	6.039	7.902	9.400	10.70	11.18	11.50	11.27	11.24	11.11

Notes: This table presents parameters estimated using the column-vintage declarations dummy variable models. These correspond to forecasts made on the date in the column header for the week ending that Saturday (two days following). These models exploit disaster declarations made up to the day prior to the date in the column header. Standard errors are omitted from the table, with ***: $p < 0.01$, **: $p < 0.05$, and *: $p < 0.1$, respectively. Parameters stabilize after five weeks due to the presence of four separate weeks of disaster declarations and that some declarations do not occur until after the forecast timing cutoff for that week. In the sixth vintage week, a final revision is made due to revisions to the prior week's data.

Table A.1: Forecasting Results

Data Structure:		State - Panel	State - Panel	State - Time Series	National	National	
Information Set:		Declaration DVs	Google Trends	Autoregression	Google Trends	Autoregression	
Week Ending	U.S. Claims	[1]	[2]	[3]	[4]	[5]	Average
14-Mar-20	250,869	200,124	200,498	210,613	200,124	209,780	204,228
21-Mar-20	2,898,392	302,526	256,555	240,715	580,881	246,751	325,486
28-Mar-20	5,823,757	4,272,739	2,893,920	1,268,139	3,735,416	1,699,932	2,774,029
4-Apr-20	6,203,348	6,472,376	9,235,556	2,798,412	7,538,163	4,621,571	6,133,216
11-Apr-20	4,971,820	5,764,621	5,413,811	4,247,836	1,979,762	5,269,418	4,535,090
18-Apr-20	4,267,394	4,418,919	5,466,608	3,897,886	6,331,850	4,230,563	4,869,165
25-Apr-20	3,489,173	3,007,053	4,270,662	3,438,980	4,243,381	3,660,814	3,724,178
2-May-20	2,849,079	3,083,641	3,297,980	2,905,236	3,699,928	3,027,102	3,202,777
9-May-20	2,345,376	2,709,145	2,605,137	2,408,037	2,006,348	2,495,679	2,444,869
16-May-20	2,174,298	2,395,143	2,171,923	2,079,470	2,744,618	2,075,898	2,293,410

Notes: This table presents forecasts made on the Thursday of the week ending on the date listed in the row. For percent errors and statistics to compare these forecasts, see Table 2.

Table A.2: Model [2] (State Google Trends) Vintage Estimates

Dependent variable: Normalized State UI Claims ($StateNormClaims$)

	Model Vintage									
Parameter	3/14/2020	3/21/2020	3/28/2020	4/4/2020	4/11/2020	4/18/2020	4/25/2020	5/2/2020	5/9/2020	5/16/2020
$\tilde{G}(t)$	-0.0260	7.228***	3.790***	3.298***	2.774***	1.140*	0.901**	0.847**	0.937**	0.937***
$G(t-1)$	0.270	-6.064**	-0.546	-0.849	-0.612	0.610	0.629	0.502	0.335	0.286
Constant	0.779***	0.864	0.0115	1.745***	2.601***	4.096***	4.580***	4.994***	4.942***	4.751***
Observations	260	312	364	416	468	520	572	624	676	728
R^2	0.008	0.607	0.637	0.643	0.591	0.480	0.427	0.381	0.358	0.337
RMSE	0.393	4.869	8.353	10.25	11.64	13.13	13.61	13.67	13.59	13.47

Notes: This table presents parameters estimated using the column-vintage declarations dummy variable models. These correspond to forecasts made on the date in the column header for the week ending that Saturday (two days following). These models exploit disaster declarations made up to the day prior to the date in the column header. Standard errors are omitted from the table, with ***: $p < 0.01$, **: $p < 0.05$, and *: $p < 0.1$, respectively.

Table A.3: Model [3] (State AR Model) Final Period Estimates

Dependent variable: Log State UI Claims (ln($StateClaims$))

State	y(t-1)	y(t-2)	y(t-3)	R^2	RMSE	State	y(t-1)	y(t-2)	y(t-3)	R^2	RMSE
Alabama	0.764***	0.0127	0.0660*	0.683	0.270	Montana	0.779***	0.0363	0.0882**	0.773	0.220
Alaska	0.687***	0.221***	0.0140	0.798	0.170	Nebraska	0.753***	0.0994*	0.0426	0.747	0.232
Arizona	0.833***	-0.0509	0.136**	0.783	0.186	Nevada	0.721***	0.157*	0.0562	0.814	0.172
Arkansas	0.769***	-0.0298	0.151***	0.732	0.231	New Hampshire	0.704***	0.136**	0.0710	0.767	0.272
California	0.612***	0.289***	0.000302	0.736	0.154	New Jersey	0.877***	-0.0265	-0.0413	0.674	0.195
Colorado	0.732***	0.132	0.0668	0.810	0.183	New Mexico	0.668***	0.154**	0.0602	0.696	0.208
Connecticut	0.824***	0.00412	-0.00446	0.667	0.224	New York	0.673***	0.0104	0.136***	0.564	0.245
Delaware	0.482***	0.145***	0.137***	0.453	0.340	North Carolina	0.684***	0.107*	0.148***	0.843	0.281
District of Columbia	0.674***	0.154***	0.108**	0.806	0.218	North Dakota	0.636***	0.154***	0.0688**	0.655	0.339
Florida	0.756***	0.0460	0.166***	0.855	0.188	Ohio	0.830***	-0.0126	0.0988**	0.799	0.201
Georgia	0.684***	0.0870*	0.130***	0.716	0.268	Oklahoma	0.544***	0.284***	0.0873	0.714	0.236
Hawaii	0.747***	0.0468	0.122**	0.761	0.189	Oregon	0.667***	0.128**	0.144**	0.820	0.171
Idaho	0.875***	-0.0338	0.0884**	0.837	0.202	Pennsylvania	0.846***	-0.0645	0.117***	0.769	0.178
Illinois	0.679***	0.214***	0.0301	0.775	0.172	Rhode Island	0.707***	0.0831	0.000152	0.594	0.288
Indiana	0.817***	0.0681	0.0438	0.824	0.239	South Carolina	0.582***	0.123***	0.157***	0.650	0.315
Iowa	0.712***	0.0391	0.137***	0.698	0.264	South Dakota	0.777***	0.155**	-0.0102	0.801	0.232
Kansas	0.541***	0.186***	0.144***	0.632	0.267	Tennessee	0.833***	-0.0481	0.0905**	0.747	0.271
Kentucky	0.759***	0.0540	0.0386	0.660	0.313	Texas	0.640***	0.145*	0.121**	0.699	0.180
Louisiana	0.772***	0.0888	0.0317	0.747	0.235	Utah	0.792***	0.0963	0.0409	0.830	0.179
Maine	0.756***	0.138*	0.0140	0.799	0.221	Vermont	0.718***	0.0344	0.0990***	0.651	0.277
Maryland	0.717***	0.162**	0.0367	0.770	0.185	Virginia	0.698***	0.177**	0.0581	0.805	0.214
Massachusetts	0.692***	0.196***	-0.0376	0.667	0.222	Washington	0.851***	0.0699	0.0404	0.858	0.146
Michigan	0.832***	0.0675	-0.0301	0.743	0.282	West Virginia	0.696***	0.0371	0.109***	0.656	0.239
Minnesota	0.852***	0.0626	0.0103	0.823	0.196	Wisconsin	0.908***	-0.240***	0.269***	0.838	0.197
Mississippi	0.768***	0.139**	0.0108	0.800	0.235	Wyoming	0.688***	0.0916*	0.142***	0.784	0.222
Missouri	0.706***	0.138***	0.0113	0.680	0.244	Puerto Rico	0.295***	0.180***	0.165***	0.248	0.585

Notes: This table presents parameters estimated using the final-period state-level autogregression models (constant terms omitted for brevity but available upon request). These correspond to forecasts made on May 14th for the week ending May 16th, which use claims data through the week ending May 9th. Standard errors are omitted from the table, with ***: $p < 0.01$, **: $p < 0.05$, and *: $p < 0.1$, respectively.

Table A.4: Models [4] and [5] (National Models) Final Period Estimates

Model	Google Trends	Autoregression
Dependent Variable	Normalized Claims	ln(Claims)
	[4]	[5]
$\tilde{G}(t)$	3.470***	
$G(t-1)$	-2.076*	
$\ln(USClaims(t))$		0.932***
$\ln(USClaims(t-1))$		0.0148
$\ln(USClaims(t-2))$		-0.0128
Constant	0.361***	0.837***
Observations	324	1,121
R^2	0.854	0.853
RMSE	1.200	0.140

Notes: This table presents parameters estimated using the final-period national models. These correspond to forecasts made on May 14th for the week ending May 16th, which use claims data through the week ending May 9th and Google Trends data through May 11th. Standard errors are omitted from the table, with ***: $p < 0.01$, **: $p < 0.05$, and *: $p < 0.1$, respectively.

Table A.5: Forecasting Results, Additional Models

Data Structure:		State - Panel	State - Panel	State - Panel	State - Panel	National
Information Set:						
Declarations		Yes	Yes	Yes		
Google Trends			Yes	Yes	Yes	Yes
Autoregression		Yes		Yes	Yes	Yes
Week Ending	National Claims	[6]	[7]	[8]	[9]	[10]
3/14/2020	250,869	-22%	-20%	-23%	-24%	-24%
3/21/2020	2,898,392	-89%	-86%	-84%	-89%	-82%
3/28/2020	5,823,757	481%	-172%	-10%	83%	-18%
4/4/2020	6,203,348	46%	41%	52%	60%	55%
4/11/2020	4,971,820	14%	-22%	-31%	-16%	-53%
4/18/2020	4,267,394	-7%	-1%	-4%	15%	29%
4/25/2020	3,489,173	-20%	-12%	-19%	6%	6%
5/2/2020	2,849,079	26%	-37%	6%	3%	15%
5/9/2020	2,345,376	12%	-50%	-3%	-1%	-32%
5/16/2020	2,174,298	3%	-19%	-4%	-1%	29%
Mean Error		-2,900,914	1,425,390	220,096	-599,623	89,740
MAE		3,623,648	1,933,248	896,692	1,288,929	1,281,982
RMSE		8,939,559	3,428,374	1,392,995	2,111,187	1,674,856
MAE-DM		-1.983**	-1.573	-2.794***	-1.821*	-3.621***

Notes: This table presents percentage forecast errors made on the Thursday of the week ending in the date listed in the row. MAE is the mean absolute forecast error. RMSE is the square-root of the mean squared forecast error. MAE-DM is the Diebold-Mariano small-sample test statistic relative to model [1] in Table 2, with ***: $p < 0.01$, **: $p < 0.05$, and *: $p < 0.1$, respectively. All statistics are at the national level, including Mean Error, MAE, RMSE, and MAE-DM, which are calculated over the 10 forecast periods. A remark on the forecast errors for 3/28 is necessary. In this week, panel models with more complex information sets are very sensitive to the jump from the previous week due to low claims variation and small sample sizes estimated up to this point.