Online Appendix:
State-Level Economic Policy Uncertainty

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Abstract

We quantify and study state-level economic policy uncertainty. Tapping digital archives for nearly 3,500 local newspapers, we construct three monthly indexes for each state: one that captures state and local sources of policy uncertainty (EPU-S), one that captures national and international sources (EPU-N), and a composite index that captures both. EPU-S rises around gubernatorial elections and own-state episodes like the California electricity crisis of 2000-01 and the Kansas tax experiment of 2012. EPU-N rises around presidential elections and in response to 9-11, Gulf Wars I and II, the 2011 debt-ceiling crisis, the 2012 fiscal cliff episode, and federal government shutdowns. Close elections elevate policy uncertainty much more than the average election. VAR models fit to pre-COVID data imply that upward shocks to own-state EPU foreshadow weaker economic performance in the state, as do upward EPU shocks in contiguous states. The COVID-19 pandemic drove huge increases in policy uncertainty and unemployment, more so in states with stricter government-mandated lockdowns.

JEL Classification: D80, E66, G18, H70, R50, R31

Keywords: policy uncertainty, elections and uncertainty, state-level economic performance, unemployment, housing starts, home prices, spatial spillovers, COVID-19 pandemic

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A Online Appendix Materials

A.1 Flagging Newspaper Articles about State-Level EPU

Table A.1 reports the terms in our Economy, Uncertainty, and National Policy term sets and in the State Policy set for Michigan. State Policy term sets differ across states in line with how they refer to legislative and judicial bodies, regulatory agencies, and state and local government officials. State Policy sets include “initiative" and “referendum" in states that have provisions for putting votes about policy matters before the citizenry. The full collection of State Policy sets is available at https://policyuncertainty.com/state_epu_terms.htm. To facilitate comparison to earlier work, Table A.1 also reports the term sets devised by Baker et al. (2016).

Media markets can extend across state borders. Thus, one might worry that a newspaper associated with State A contains many articles about policy uncertainty in a bordering State B, simply because the paper has significant readership in B. We exclude newspapers with national reach, precisely because it’s unclear how to situate them geographically. For example, Investor’s Business Daily, the New York Times, USA Today, Wall Street Journal, and Washington Post are not in our sample. Of course, there are other newspapers with readerships in more than one state. We have no effective way to precisely measure the geography of each paper’s readership. Instead, as a simple check, we identified the newspapers in our sample that publish in Metropolitan Statistical Areas that span more than one state. These multi-state MSA papers publish in places like New York, DC, Chicago, and Philadelphia. There are fewer than 60 such papers in our entire sample. Especially because we do not weight by circulation when aggregating over newspapers, there are too few of these papers to seriously distort our state-level EPU measures. Moreover, if multi-state readership were to cause newspaper coverage of policy uncertainty to bleed over to bordering states in a large way, we would expect to see stronger EPU co-movements for neighboring states. However, we find no such pattern in the dyadic regression analysis reported in Section 2.6.

A.2 State-Level EPU Coverage and Additional Descriptive Statistics

For each state, Table A.2 reports the sample start year for our $EPU\text{-}S$, $EPU\text{-}N$, $EPU\text{-}C$, and $EPU\text{-}BBD$ indexes, the minimum and maximum number of newspapers that feed into the index construction, and the average circulation of the newspapers used to construct the indexes in 2016. Figure A.1 plots the average between-state EPU correlations in rolling samples of the last

60 observations. The top and bottom panels show, respectively, the average of the pairwise level and change correlations. The 9-11 attacks, the financial crisis in September 2008, the onset of the COVID pandemic, and (to a lesser extent) the November 2016 election victory of Donald Trump brought abrupt increases in the average pairwise correlations.

Figure A.2 shows how each state's EPU measures correlate with their national-average counterparts. Figure A.3 displays histograms of one-month log changes, $\ln(EPU\text{-}N_{s,t}/EPU\text{-}N_{s,t-1})$, in response to selected national and international events, where s indexes states as before and t is the event month. Figure A.4 shows the average ratio of $EPU\text{-}S$ to $EPU\text{-}N$ by state before and after the COVID pandemic struck.

A.3 VAR Models, Identification, and Additional Results

This section of the appendix describes our structural VAR models, articulates the assumptions we adopt to identify them, and presents additional results referenced in the main text.

Recall that we fit panel VAR models by OLS to monthly data on $\mathbf{Y_{st}} = (\ln(EPU\text{-}C_{st}), UN_{st})'$, where UN_{st} is the unemployment rate for state s in month t, and $\ln(EPU\text{-}C_{st})$ is the natural log of the state's composite EPU index value in month t.[26] We treat $\ln(EPU\text{-}C_{st})$ and UN_{st} as covariance stationary processes. Our baseline structural VAR model is

$$\mathbf{Y_{st}} = \tilde{\alpha}_\mathbf{s} + \sum_{\mathbf{i=1}}^{\mathbf{6}} \mathbf{A_i Y_{s,t-i}} + \mathbf{B}\epsilon_\mathbf{st}, \tag{A.1}$$

where $\epsilon_{st} = (\epsilon_{st}^{EPU}, \epsilon_{st}^{UN})'$ is a 2x1 vector of serially and mutually uncorrelated structural innovations, $\mathbf{A}_i$ and $\mathbf{B}$ are 2x2 coefficient matrices common across states, and $\tilde{\alpha}_s$ is a 2x1 vector of state-specific constants.

This structural VAR embeds two assumptions that warrant brief remarks. First, it neglects spatial interactions, e.g., own-state shocks with spillover effects on other states. We relax this assumption in Section 4.4. Second, following standard practice, we assume for each s that $\text{corr}(\epsilon_{st}^{EPU}, \epsilon_{st}^{UN}) = 0$ in the time-series dimension. Although it often passes without mention in the structural VAR literature, the assumption of contemporaneously uncorrelated structural innovations (for a given geographic unit) is a substantive restriction. See Davis and Haltiwanger (1999) for discussion and

[26]The main text also considers VARs with $\ln(EMP_{st})$ in place of UN_{st}, where EMP_{st} denotes employment in state s and month t. We couch the discussion here in terms of the unemployment rate for the sake of concreteness.

an analysis of identification when relaxing this assumption.

Given (A.1), we consider various assumptions to identify the structural innovations – "shocks," as we call them in the main text. For example, to obtain the impulse response functions in Figure 5, we posit a recursive structure that lets us decompose the reduced-form VAR errors (i.e., the OLS regression residuals) according to $\mathbf{e}_{st} = \mathbf{B}\epsilon_{st}$:

$$\mathbf{e}_t \equiv \begin{pmatrix} e_{st}^{EPU} \\ e_{st}^{UN} \end{pmatrix} = \begin{bmatrix} 1 & 0 \\ b_{21} & 1 \end{bmatrix} \begin{pmatrix} \epsilon_{st}^{EPU} \\ \epsilon_{st}^{UN} \end{pmatrix} \tag{A.2}$$

That is, we identify shocks by placing ln$(EPU\text{-}C)$ first in a recursive causal ordering. Assumption (A.2) also suffices to identify the elements of the $\mathbf{A}$ matrices in (A.1).

Inverting the identified structural VAR yields its moving-average representation for state s,

$$\mathbf{Y_{st}} = \alpha_\mathbf{s} + \sum_{\mathbf{i=0}}^{\infty} \mathbf{C_i}\epsilon_{\mathbf{s,t-i}} \tag{A.3}$$

The elements in the first column and second row of the $\mathbf{C}_i$ matrices give the dynamic responses of $UN_{s,t+i}$ to a unit-size ϵ_{st}^{EPU} shock for $i = 0, 1, 2, ...$, as plotted in Figure 5.

Figures A.5, A.6 and A.7 report additional VAR-based results referenced in Section 4.1. To obtain the response functions displayed in Figure A.5, we fit the reduced-form VAR separately for each state and rely on recursive ordering (A.2) to recover structural VARs with distinct $\mathbf{A}_i$ and $\mathbf{B}$ matrices for each state, which yields the state-specific dynamic response functions plotted in the figure. For Figure A.6, we alter the lag lengths in the baseline VAR model (A.1), as indicated in the figure, and again rely on the recursive ordering (A.2) for identification. For Figure A.7, we place ln$(EPU\text{-}C)$ last in the recursive causal ordering to identify (A.1).

Figure 6 in Section 4.3 reports a VAR-based historical decomposition of fluctuations in California's unemployment rate. To obtain this decomposition, we fit a VAR to the monthly data for California and place ln$(EPU\text{-}C)$ last in the recursive causal ordering to identify structural shocks and obtain the structural VAR. We then use the Wold moving-average representation of the structural VAR to obtain the model-implied contributions of the shocks (i.e., past and current values of ϵ_t^{EPU} and ϵ_t^{UN}) to the deviation of California's unemployment rate from its equilibrium value at each t. See slides 76 and 77 in Cesa-Bianchi (undated) for an explicit statement of the decomposition. Figure A.8 displays the dynamic response of California's unemployment rate to a unit standard deviation shock in its own ln$(EPU\text{-}C)$ value.

Figures A.9 and A.10 display dynamic response functions to own-state ln$(EPU\text{-}C)$ shocks for the expanded VAR specifications discussed in Section 4.5.

A.4 Measuring the Stringency of Government Lockdown Orders

We obtain daily state-level data on shelter-in-place orders (SIPOs), non-essential business closure orders (BCOs), restaurant closure orders (RCOs), and school closure orders (SCOs) from the Kaiser Family Foundation (KFF) at https://www.kff.org/report-section/state-covid-19-data-and-policy-actions-policy-actions/ (accessed November 2021). We average the daily state-level values to calendar months. If a given order type was in place during only part of the month, we discount the corresponding indicator value accordingly. For example, if a state had a shelter-in-place order in effect for half the month, we set its $SIPO$ value for that month to one-half.

For April and May 2020, we use data with more geographic granularity. In particular, we obtain weekly, county-level data on SCOs from Keystone Strategy at https://www.keystonestrategy.com/coronavirus-covid19-intervention-dataset-model/ (accessed 28 October 2020). We obtain county-level data for SIPOs, BCOs, and RCOs from Goolsbee et al. (2020), who provide the dates on which these orders went into effect and were lifted. We use their dates to determine whether a given order type was in effect for each county by week, regardless of whether the order originated at the state or county level.[27] We then aggregate county-level indicator values for April and May 2020 to the state level using county-level population shares.[28]

Armed with our monthly state-level values for $SIPO$, BCO, RCO and SCO, we plug them into equation (5) in the main text to obtain monthly, state-level values for our Lockdown Stringency Index. As a final step, we average over months in the calendar quarter for each state to obtain the quarterly, state-level index values.

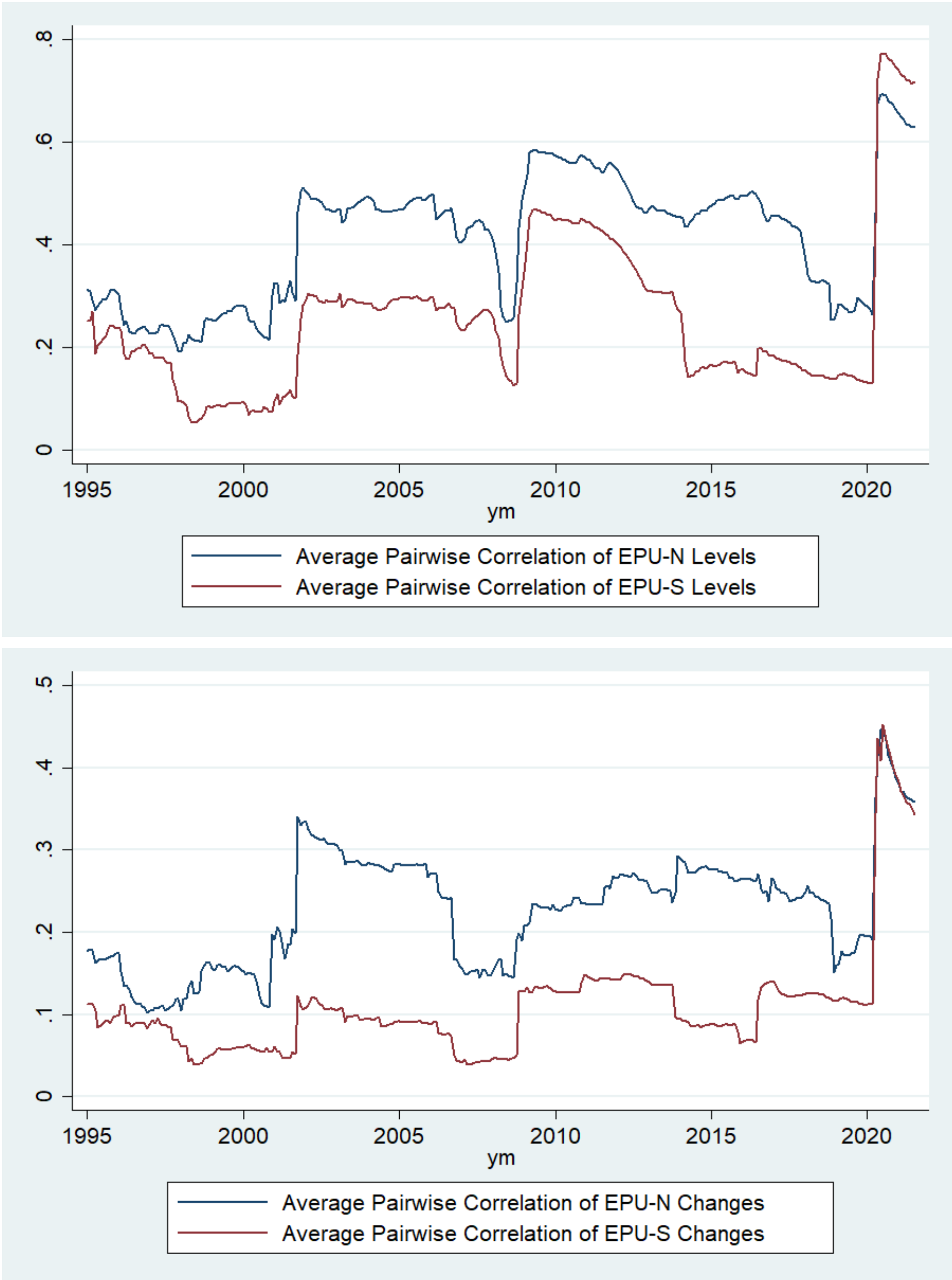
[27] In some instances, their observations reflect city-level government orders. We omit city-level orders that do not extend to the entire county. The Goolsbee et al. (2020) data end in May 2020, which precludes us from extending the granular geographic approach beyond that month.

[28] When aggregating over counties to obtain a state-level SCO value, we restrict attention to counties with SCO data. In effect, we treat missing SCO data as missing at random. In practice, this assumption is unlikely to matter much, because counties with SCO data account for most of the population.

A.5 Additional Material for Section 5

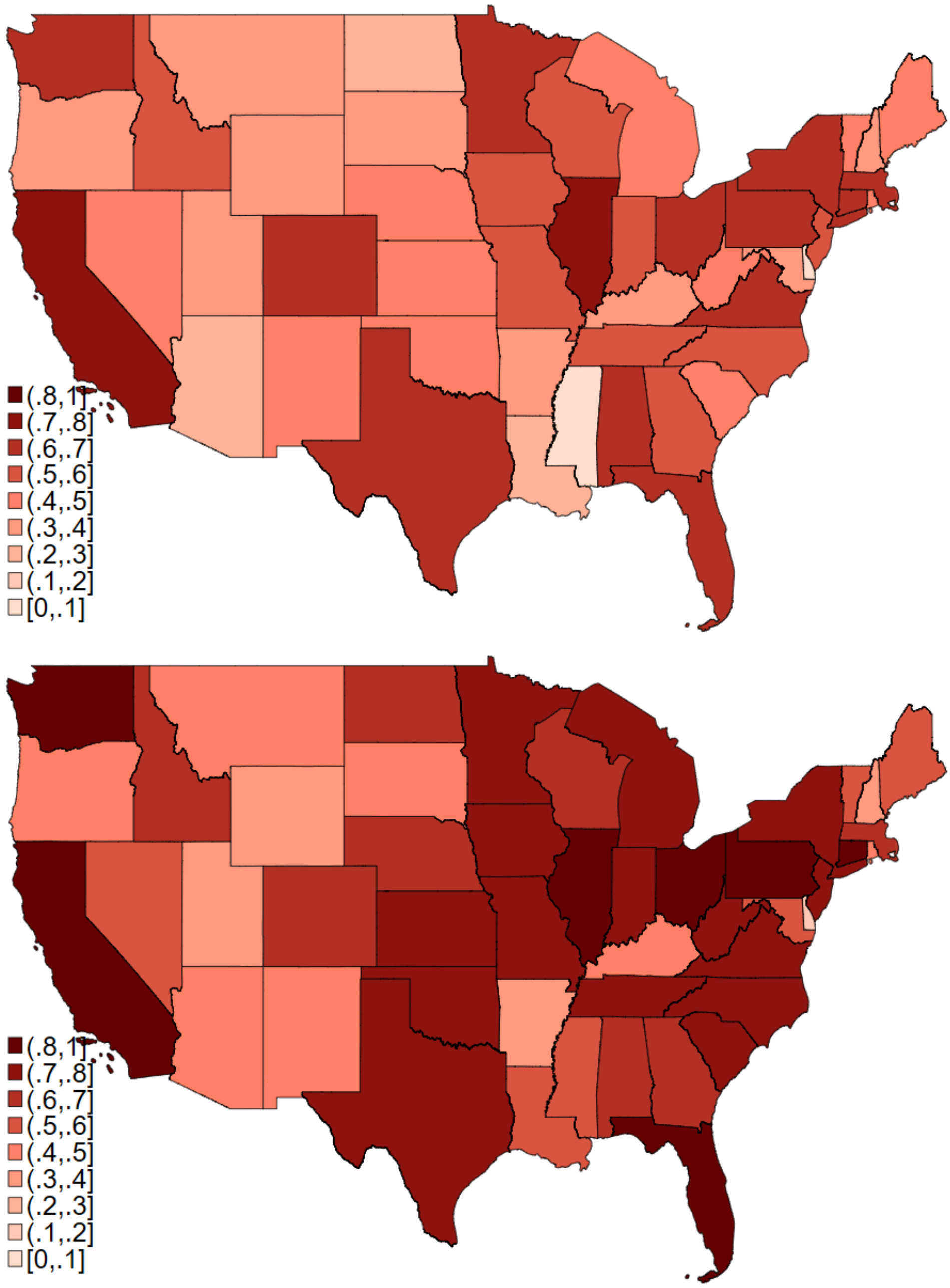
Table A.3 reports summary statistics for the variables used in the regression analyses reported in Tables 2 and 3 in the main text. Figure A.11 displays scatter plots that supplement the regression results reported in Table 2.

Figure A.1: Average Between-State Correlations of the EPU Measures, Levels and Changes



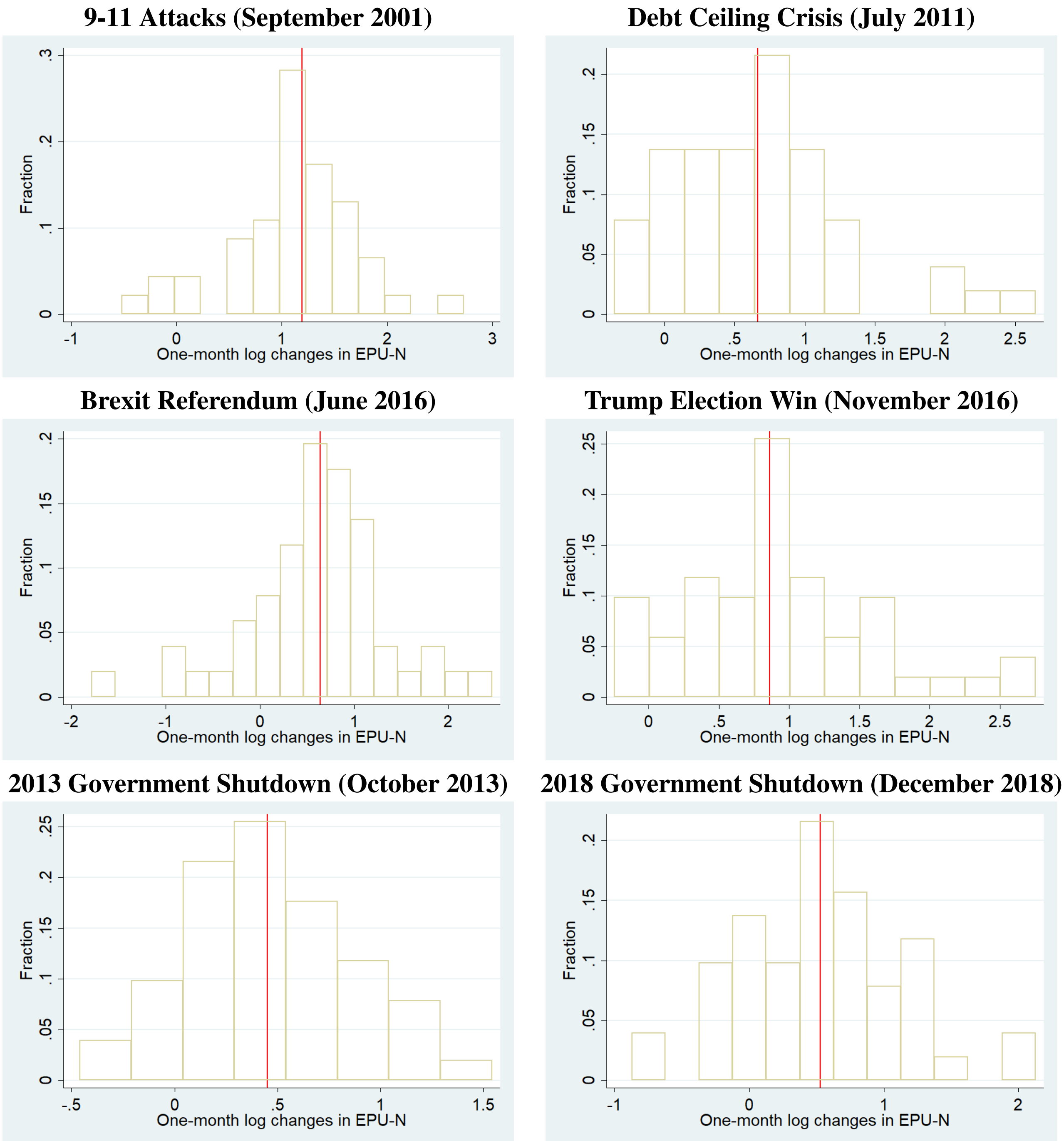
Notes: The top panel reports the average pairwise between-state correlation of the EPU-S values (red) and the EPU-N values (blue) by month. The bottom panel reports the average pairwise between-state correlations of monthly changes in the EPU-S and EPU-N values. We compute the pairwise correlations using backward 60-month rolling windows.

Figure A.2: Correlations of State-Level EPU-S and EPU-N Values with National Averages



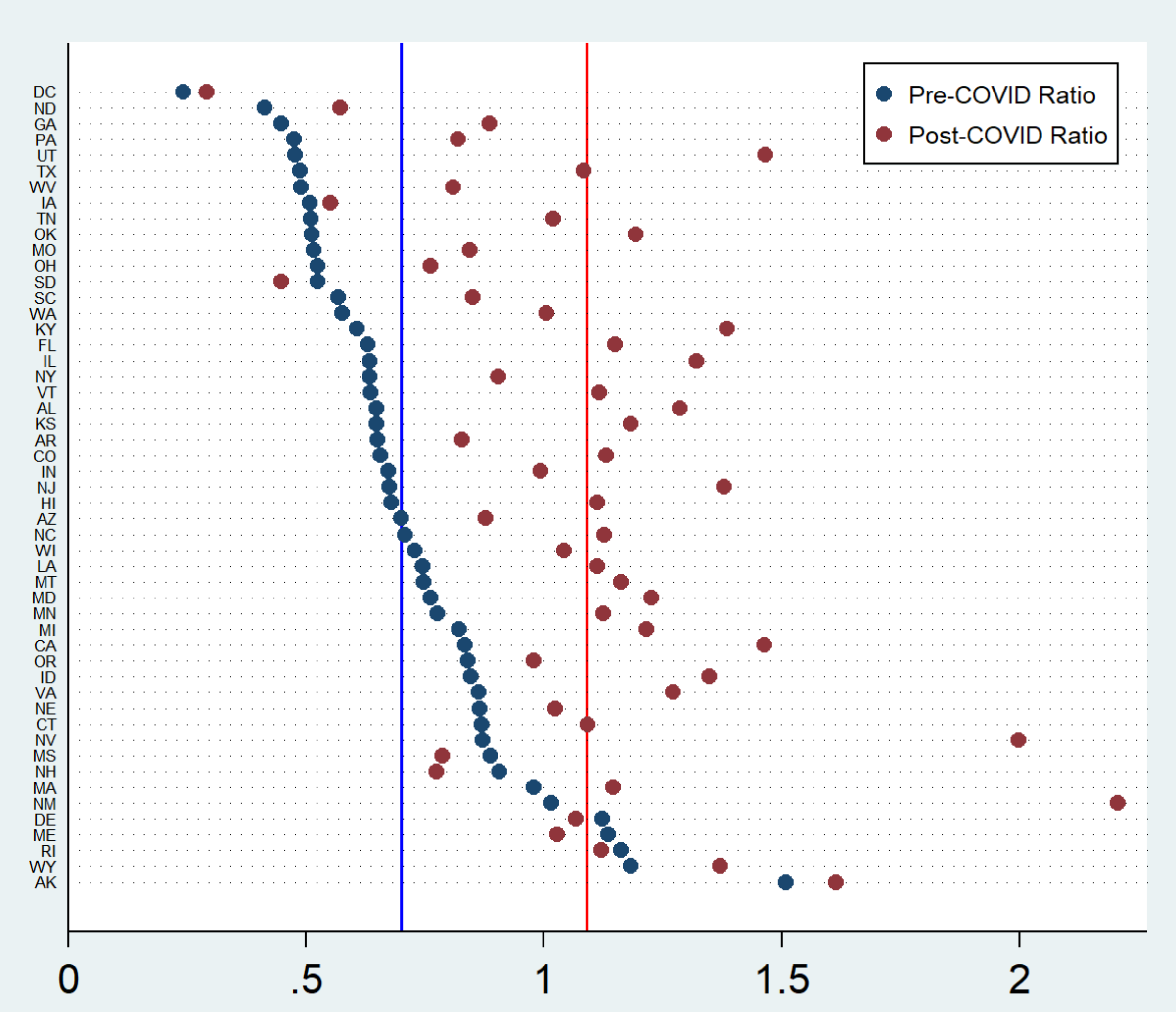
Notes: The top chart shows a heat map for the correlation of each state's EPU-S measure with the national EPU-S value, computed as the equal-weighted average of the EPU-S values across states. The bottom chart shows the analogous heat map for EPU-N. We calculate the correlations using all available months for each state from January 1990 to December 2019. EPU-S and EPU-N correlations are 0.54 and 0.59 for Hawaii and 0.25 and 0.23 for Alaska.

Figure A.3: Histograms of State-Level EPU-N Responses to National and International Events



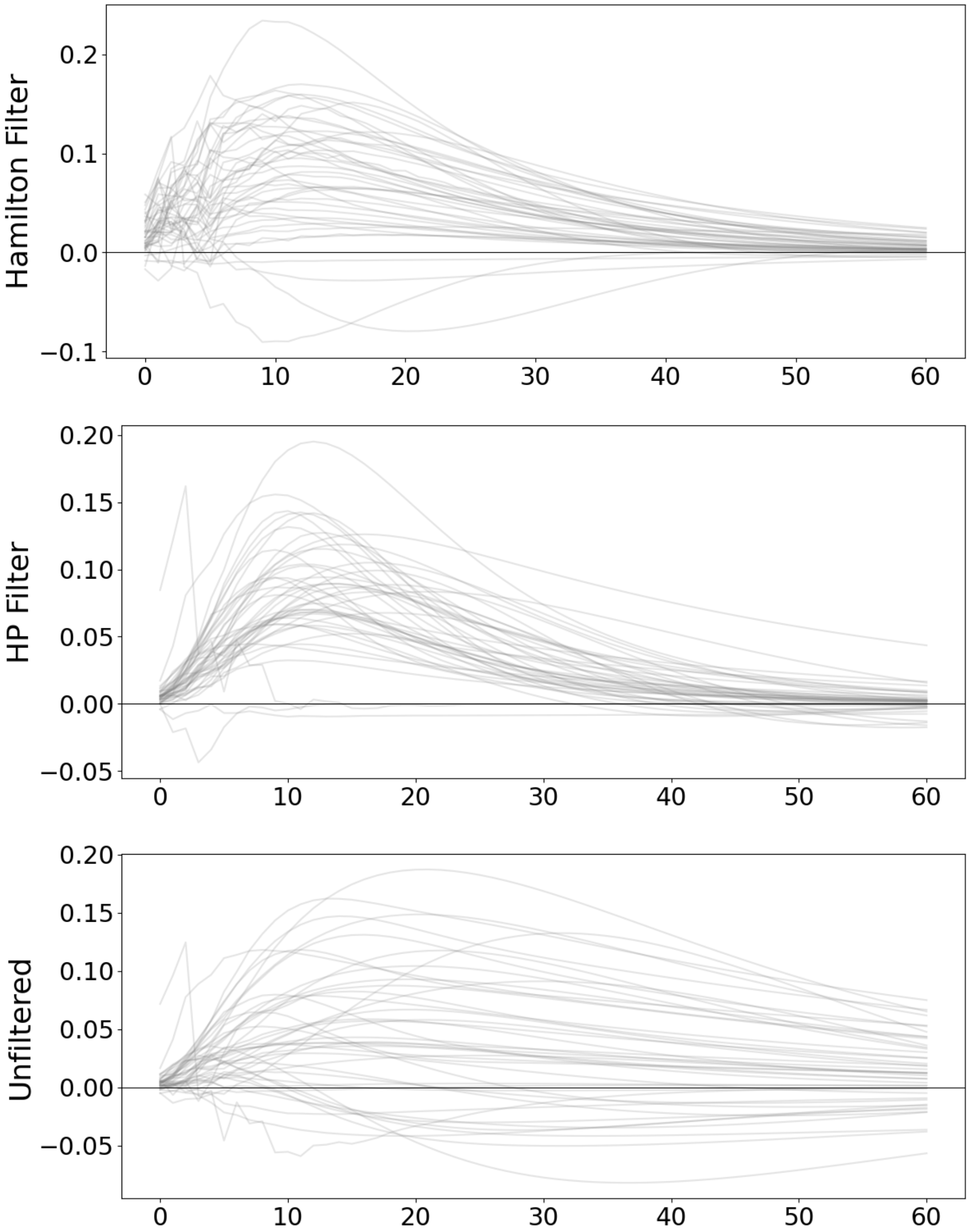
Notes: Each panel shows the fraction of states with $\ln(EPU\text{-}N_{s,t}/EPU\text{-}N_{s,t-1})$ values in the indicated bins (width = 25 log points), where t is the year and month stated in the panel heading.

Figure A.4: Average Ratio of $EPU\text{-}S$ to $EPU\text{-}N$ by State and Period



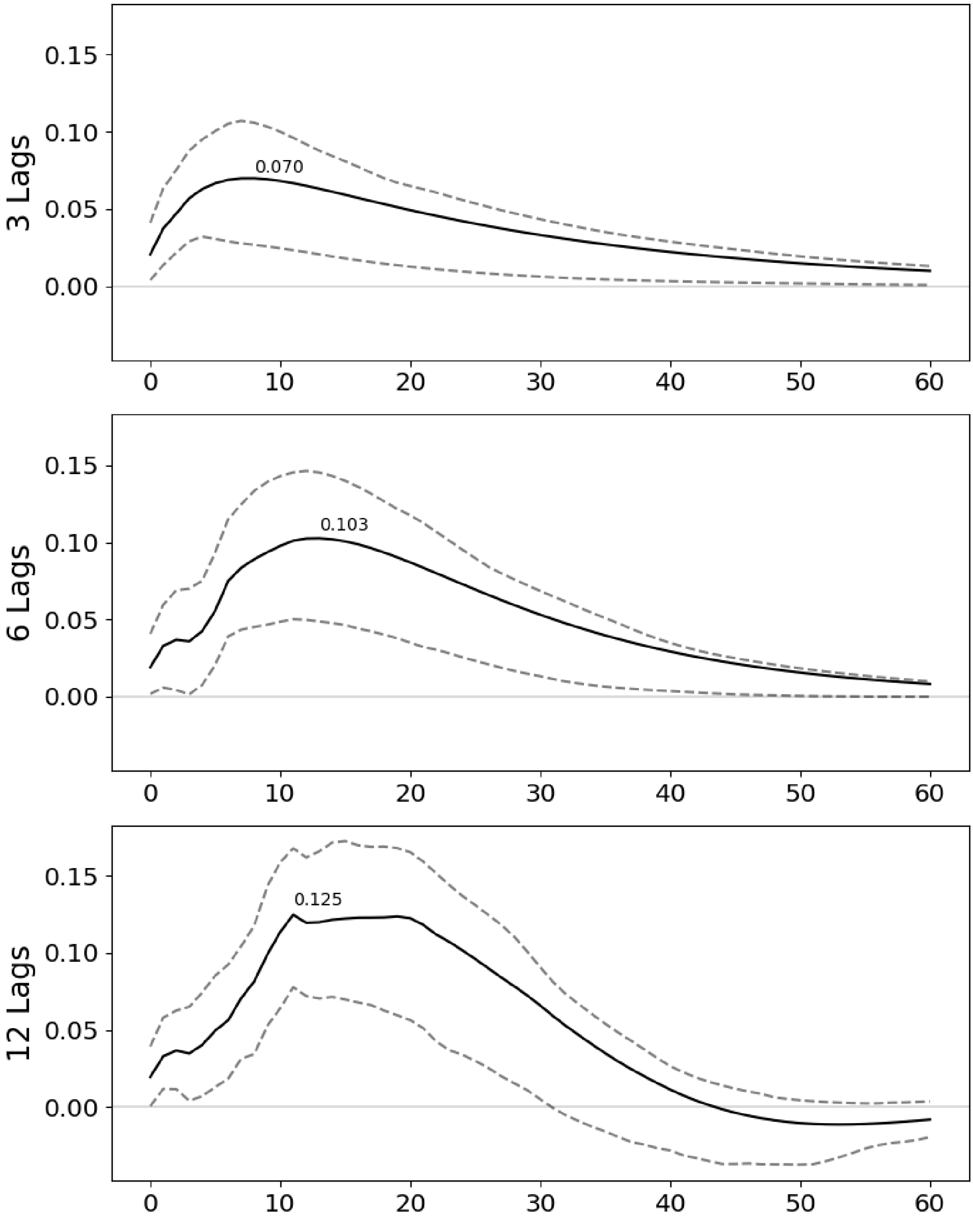
Notes: Red dots show average monthly ratios of $EPU\text{-}S$ to $EPU\text{-}N$ by state in the post-COVID period from March 2020 to June 2021. Blue dots show average ($EPU\text{-}S/EPU\text{-}N$) values in the pre-COVID period before March 2020. Sample start dates in the pre-COVID period vary across states from 1985-2006, as listed in Appendix Table A.2. We order states by the average pre-COVID values of ($EPU\text{-}S/EPU\text{-}N$).

Figure A.5: Unemployment Rate Responses to Unit Standard Deviation Own-State ln$(EPU\text{-}C)$ Shocks, Using a Separate VAR Model for Each State



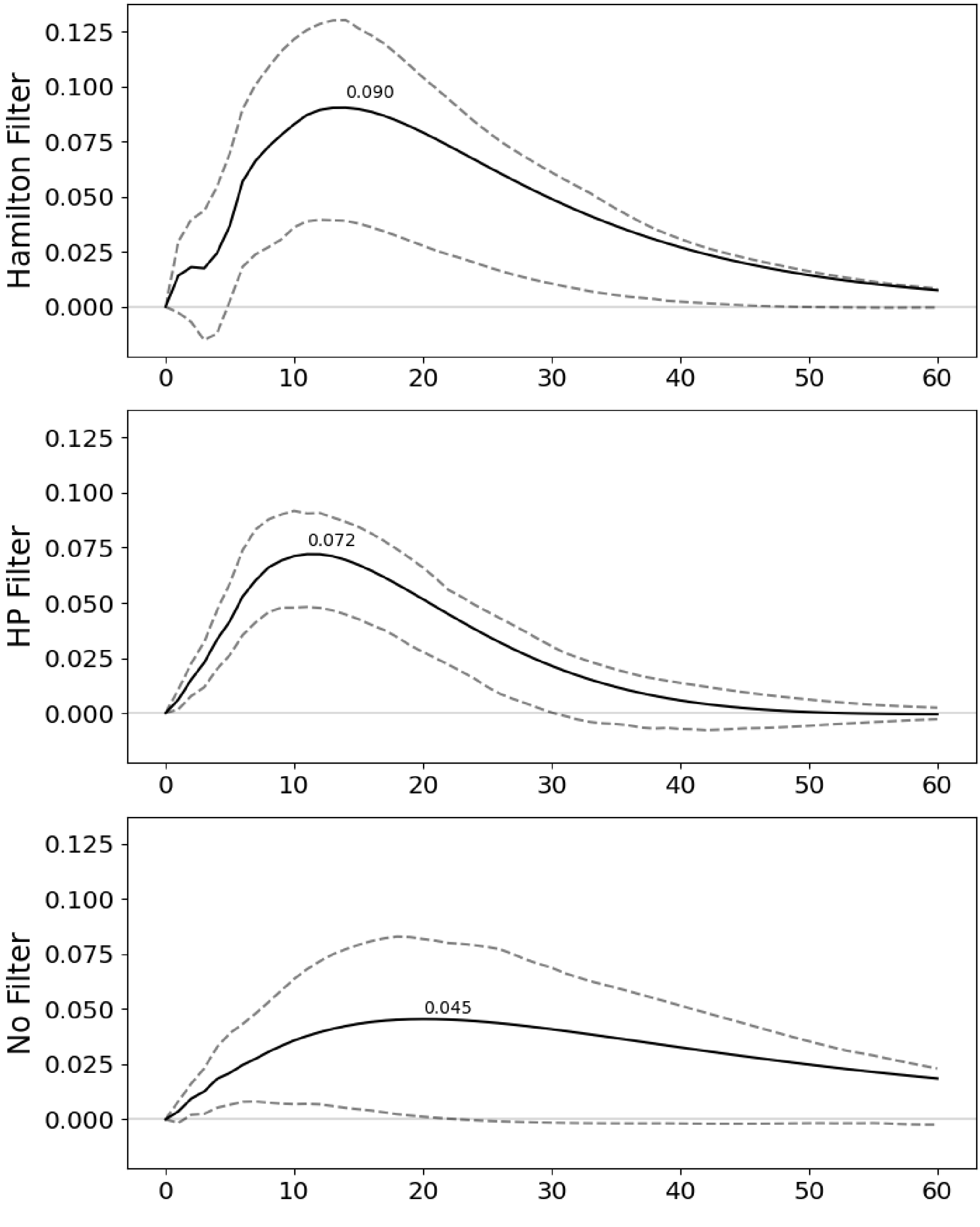
Notes: We fit a separate six-lag VAR for each state using the same data as in Figure 5. We identify the structural VARs by placing ln$(EPU\text{-}C)$ first in a recursive ordering. Each line in one of the charts shows a single state's dynamic unemployment rate response to a unit standard deviation innovation in the state's identified policy uncertainty shock.

Figure A.6: Unemployment Rate Responses with Alternative Lag-Length Specifications



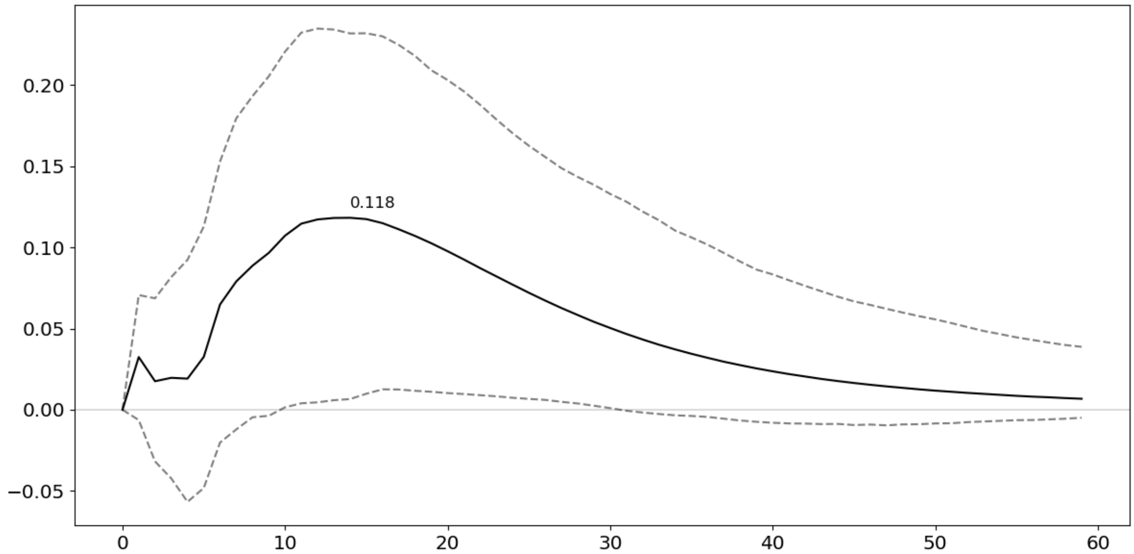
Notes: The middle chart is identical to the upper right chart in Figure 5, which uses Hamilton-filtered data. The other two charts report unemployment rate response functions for otherwise identical models that consider shorter or longer lag-length specifications, as indicated. See the notes to Figure 5 for additional information.

Figure A.7: Unemployment Rate Responses with Alternative Recursive Ordering



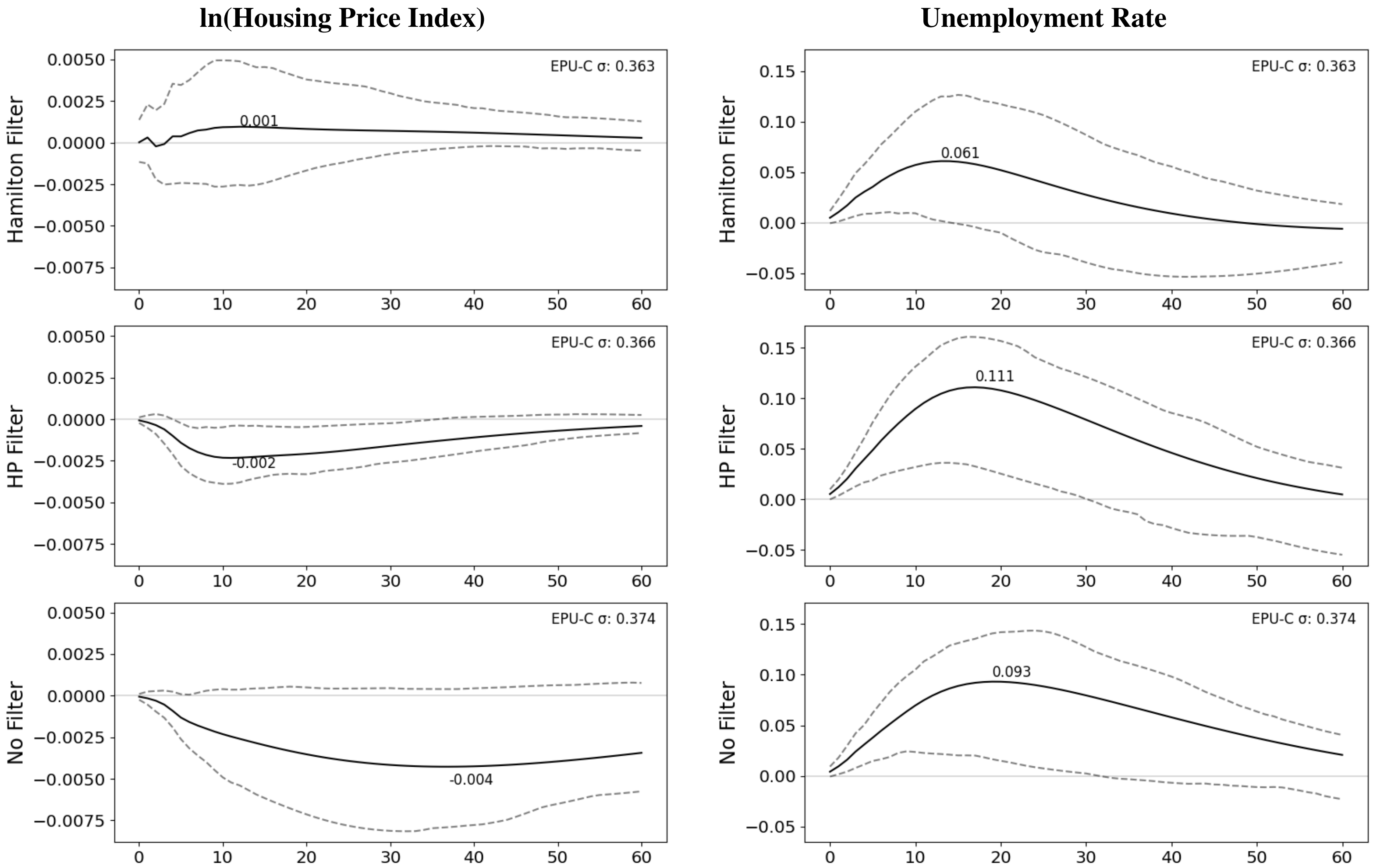
Notes: We place $\ln(EPU\text{-}C)$ last in the recursive ordering. Otherwise, the VAR models behind the response functions in this figure are identical to the ones used in the right column of Figure 5.

Figure A.8: Dynamic Response of California's Unemployment Rate to a Unit Standard Deviation Policy Uncertainty Shock



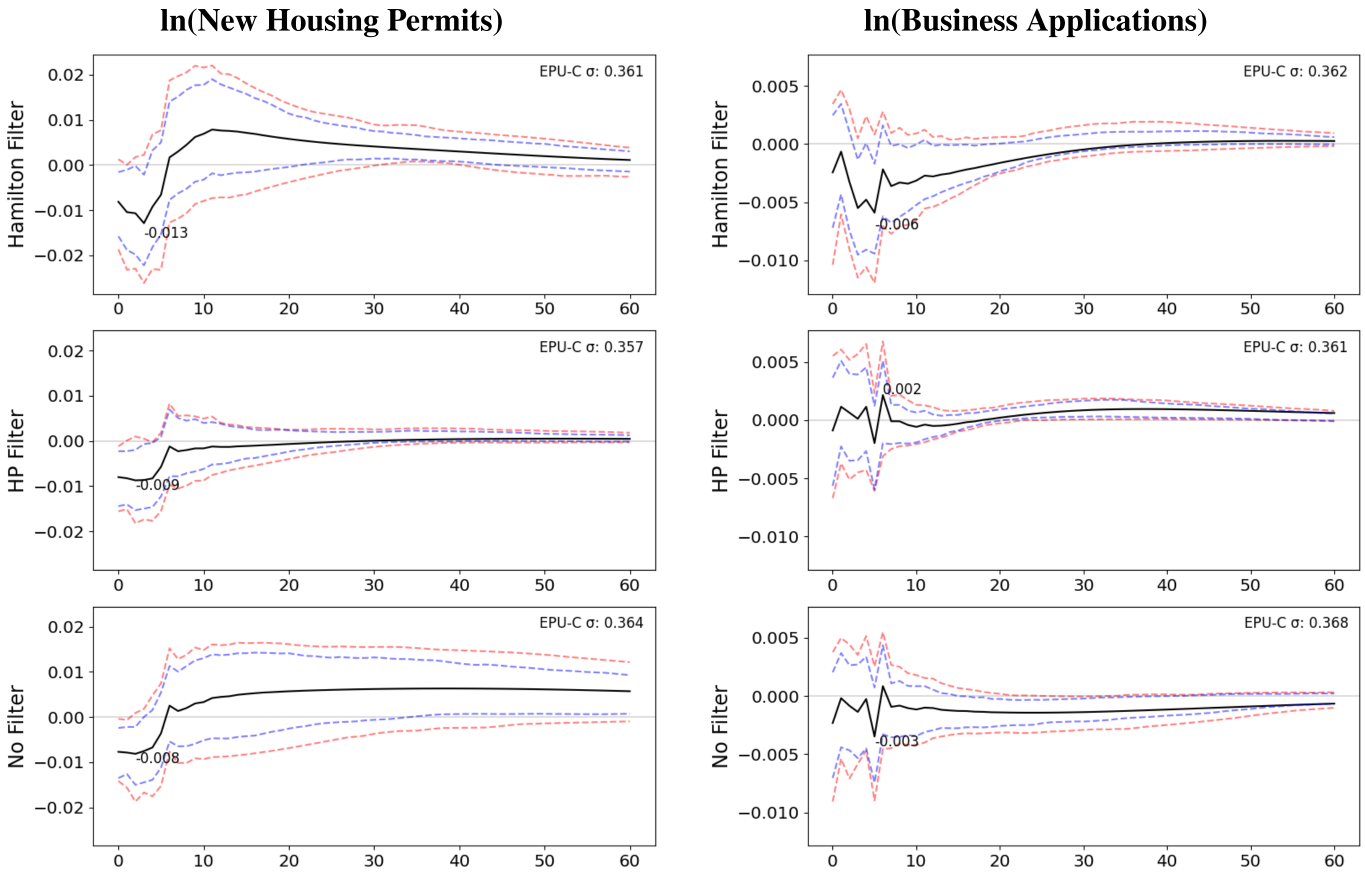
Notes: This figure shows the dynamic response of the unemployment rate to a unit standard deviation (0.28) policy uncertainty shock obtained from a structural VAR system fit to Hamilton-filtered monthly data on the unemployment rate and ln(EPU-C) for California from June 1988 to December 2019. Our unfiltered data are available from January 1985. In filtering the data, we adopt Hamilton's recommendation to look back over a two-year business cycle (h=24) with one year of lags (p=12), which uses 35 observations. Since we use an additional six lags in the VAR, our estimation sample starts in June 1988 and runs through December 2019. We recover structural shocks from the reduced-from VAR by placing ln(EPU-C) last in a recursive causal ordering of the reduced-form VAR innovations. Reversing the causal ordering yields a very similar response function.

Figure A.9: Housing Price Index and Unemployment Rate Responses to Unit Standard Deviation ln(EPU-C) Shocks



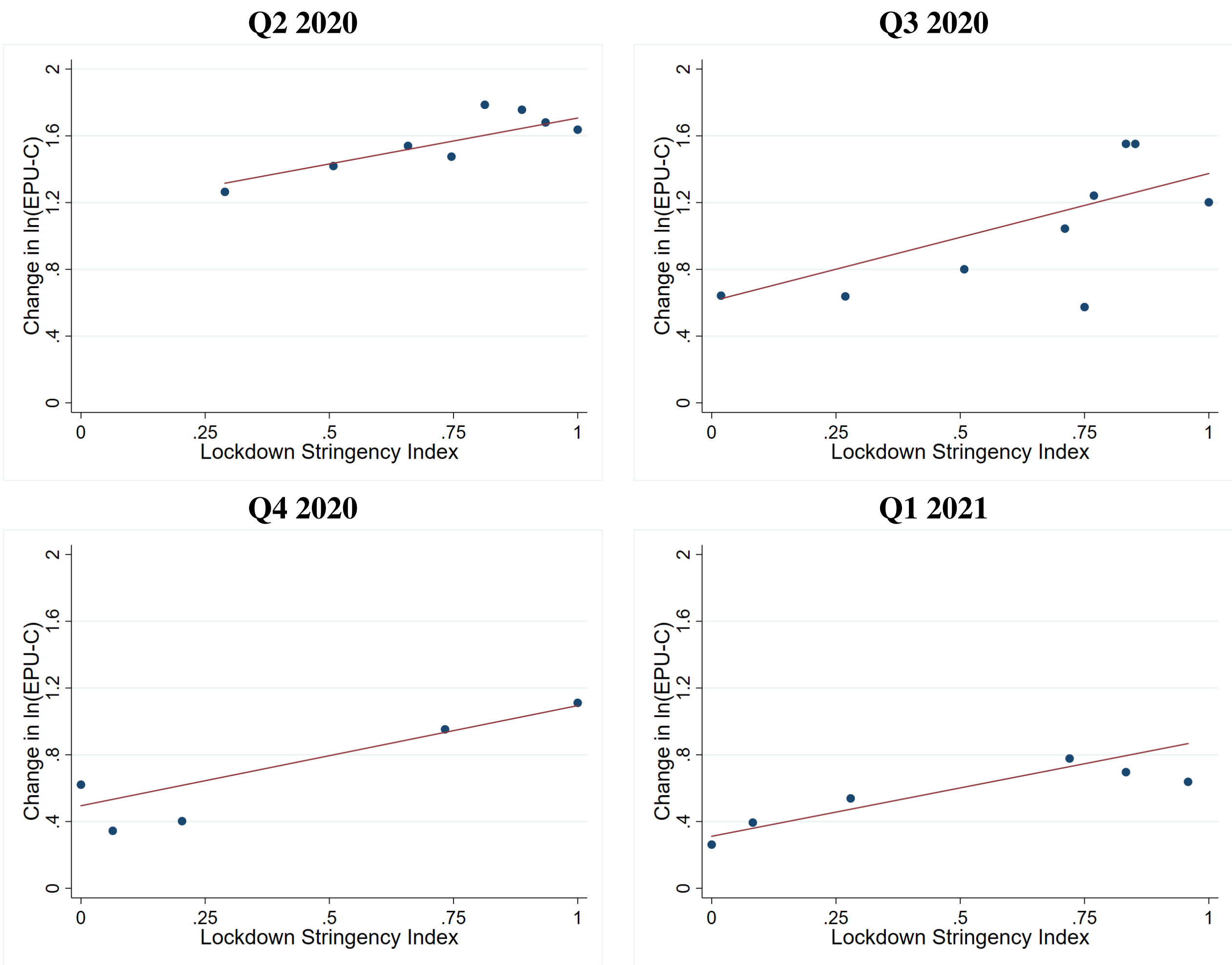
Notes: Each panel shows estimated dynamic responses of the activity measure to a unit standard EPU-C shock (with 95% confidence intervals), the peak response, and standard deviations of the identified shocks. To obtain these results, we filter the data as indicated, fit a three-equation panel VAR model by least squares to monthly state-level data for the 12 largest states by population, and place EPU-C first and the Housing Price Index last in a Cholesky ordering. The VAR system has six lags of each variable and state-specific intercepts. The estimation sample for all models runs from December 2000 to December 2019.

Figure A.10: New Housing Permits and Business Applications Responses to Unit Standard Deviation ln(EPU-C) Shocks



Notes: Each panel shows estimated dynamic responses of the activity measure to a unit standard EPU-C shock (with 95% (red) and 85% (blue) confidence intervals), the peak response, and standard deviations of the identified shocks. To obtain these results, we filter the data as indicated, fit two separate three-equation panel VAR models by least squares to monthly state-level data for the 12 largest states by population, and place EPU-C first, with New Housing Permits last in the left panel, and High-Propensity Business Applications last in the right panel, in a Cholesky ordering. The VAR system has six lags of each variable and state-specific intercepts. The estimation sample for new housing permits runs from December 2002 to December 2019, and business applications from June 2007 to December 2019.

Figure A.11: How Log Changes in $EPU\text{-}C$ from 2019 to the Indicated Quarter Vary with Lockdown Stringency Index Values in the Quarter, Bin Scatters of State-Level Observations



Notes: There are 51 underlying state-level observations for each panel. See main text for explanations of how we measure $EPU\text{-}C$ and the Lockdown Stringency Index.

Table A.1: Term Sets

	Terms
Economy	economic, economy
Uncertainty	uncertainty, uncertainties, uncertain
Policy Sets:	
EPU-N	White House, Congress, Congressional, Federal Reserve, The Fed, Monetary Policy, Veterans Affairs, Veterans Health Administration, NIH, FTC, Patent and Trademark Office, USDA, IRS, Department of Defense, National Security, Department of Homeland Security, FDA, Federal Housing Administration, SEC, CFPB, Department of Labor, Small Business Administration, NLRB, Immigration and Customs Enforcement, Immigration and Naturalization service, EPA, FERC, HUD, Bureau of Land Management, Department of Interior, Department of Education, FCC, Fish and Wildlife Service, Department of Transportation, US Treasury, Department of Treasury, DoJ, Department of Commerce, Department of Energy, Presidential election, Congressional election
EPU-S (Michigan)	Legislature, State House of Representatives, Michigan House of Representatives, State Senate, Michigan Senate, Governor, State Attorney General, Michigan Attorney General, zoning, mayor, city council, town council, initiative, referendum, Department of Labor and Economic Growth, Michigan Department of Environmental Quality, Michigan Department of Public Health, Michigan Charitable Gaming, Michigan Lottery, Michigan Gaming Control Board, Minnesota DPS Gambling Enforcement, Michigan Public Service Commission, Michigan Insurance Division, Michigan Office of Financial and Insurance Regulation, Corporations, Securities and Commercial Licensing Bureau, Michigan Department of Transportation
EPU-BBD	regulation, deficit, white house, legislation, congress, federal reserve, the fed, regulations, regulatory, deficits, congressional, legislative, legislature

Notes: In practice, we include the full names of listed agencies as well as common abbreviations (e.g., both IRS and Internal Revenue Service). We display the EPU-S policy term set for Michigan as an example. In practice, we tailor each EPU-S policy term set to the. state in question. The full collection of EPU-S policy term sets is available at https://policyuncertainty.com/state_epu_terms.html.

Table A.2: Newspaper Counts, Circulation, and Start Dates by State

State	Circulation	Paper Count		Sample	State	Circulation	Paper Count		Sample
		Min	Max	Start			Min	Max	Start
AK	257,723	4	14	2000	MT	344,620	5	6	2000
AL	698,084	4	42	1993	NC	1,966,247	2	97	1989
AR	681,028	18	43	2003	ND	110,357	2	19	1996
AZ	839,596	7	15	2001	NE	491,303	1	15	1985
CA	10,455,620	6	128	1985	NH	402,893	1	8	1997
CO	1,506,538	3	30	1990	NJ	2,633,831	1	35	1985
CT	1,370,828	2	32	1995	NM	316,147	2	19	1996
DC	221,255	1	1	1990	NV	1,316,367	4	15	2001
DE	221,762	1	8	2006	NY	6,025,416	5	65	1986
FL	4,632,859	2	67	1985	OH	3,047,598	2	61	1985
GA	1,733,399	1	47	1985	OK	646,373	3	33	1990
HI	704,357	5	8	2004	OR	979,874	1	30	1991
IA	535,134	3	29	1995	PA	4,852,690	3	75	1985
ID	303,349	8	11	2000	RI	375,397	1	9	1985
IL	4,243,258	1	94	1985	SC	811,249	1	36	1987
IN	1,159,771	5	54	1991	SD	113,493	3	9	2006
KS	399,954	2	28	1990	TN	943,871	2	30	1990
KY	568,867	2	35	1990	TX	7,660,621	2	92	1985
LA	818,192	2	28	1990	UT	492,209	1	11	1988
MA	2,356,844	1	49	1988	VA	1,681,519	1	41	1985
MD	1,312,260	2	18	1993	VT	161,276	3	10	2001
ME	294,064	1	6	1992	WA	1,746,418	1	26	1985
MI	2,381,031	6	58	1998	WI	1,002,215	3	26	1989
MN	2,084,738	2	23	1990	WV	315,008	2	22	1996
MO	1,639,738	1	36	1988	WY	61,303	3	5	2006
MS	379,829	8	27	2001					

Notes: The reported statistics pertain to the daily and weekly newspapers that we tap in the Access World News Newsbank database. Circulation figures refer to all covered papers in the state as of 2016. Average Start refers to the average date that coverage begins across the papers that we use, rounded to the nearest year. Min and Max Paper Count refer to the minimum and maximum number of papers across all sample months for the indicated state.

Table A.3: Summary Statistics for the State-Level Variables in Tables 2 and 3

Variable	Quarter = q	N	Mean	Standard Deviation
$EPUC_q$ - $EPUC_{2019}$	Q2 2020	51	1.58	0.33
$EPUC_q$ - $EPUC_{2019}$	Q3 2020	51	1.08	0.44
$EPUC_q$ - $EPUC_{2019}$	Q4 2020	51	0.82	0.43
$EPUC_q$ - $EPUC_{2019}$	Q1 2021	51	0.59	0.50
$EPUC_q$ - $EPUC_{2019}$	Q2 2021	51	0.13	0.43
COVID Deaths Per 100,000	Q2 2020	51	10.6	12.1
COVID Deaths Per 100,000	Q3 2020	51	6.75	5.20
COVID Deaths Per 100,000	Q4 2020	51	17.82	9.47
COVID Deaths Per 100,000	Q1 2021	51	16.40	6.89
COVID Deaths Per 100,000	Q2 2021	51	3.92	1.91
Lockdown Stringency Index	Q2 2020	51	0.77	0.24
Lockdown Stringency Index	Q3 2020	51	0.62	0.32
Lockdown Stringency Index	Q4 2020	51	0.55	0.34
Lockdown Stringency Index	Q1 2021	51	0.48	0.35
Lockdown Stringency Index	Q2 2021	51	0.26	0.29
Unemployment Rate	Q2 2020	51	11.73	3.29
Unemployment Rate	Q3 2020	51	7.98	2.35
Unemployment Rate	Q4 2020	51	6.25	1.82
Unemployment Rate	Q1 2021	51	5.65	1.76
Unemployment Rate	Q2 2021	51	5.27	1.61

Notes: See main text for data sources and explanations of how we construct the variable values.