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Unemployment claims during COVID-19 and economic support measures in the U.S.

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ABSTRACT

Governments want to know how effective COVID-19 anti-contagion policies and implemented economic stimulus measures have been to plan their short-run interventions. We condition on the state of the pandemic to assess the impact of non-pharmaceutical interventions and economic stimulus policies on the excess unemployment insurance claims in the United States. We focus on weekly data between February 2020 and January 2021 and motivate our analysis by the theoretical framework of the second-wave SIR-macro type models to build a panel Vector AutoRegressive (VAR) specification. Non-pharmaceutical interventions become effective immediately and impact the labor market negatively. Economic stimulus takes about a month to turn effective and only partially eases the economic welfare losses. Health-related restrictive measures are primarily driven by the state of the pandemic. Economic support policies depend predominantly on the reaction of the labor market rather than the severity of the pandemic itself.

1. Introduction

The U.S. is among the countries more severely hit by the COVID-19 pandemic. With more than 79.5 million infections and 976,516 deaths (April 9, 2022), it has the highest number of confirmed infections and the highest official death toll in the world.[1] Local state governments deployed drastic anti-contagion policy actions to shield public health in the form of social distancing measures and national lockdowns. By April 20th, 2020, forty out of the fifty states had adopted state-wide lockdowns. Such containment measures, although effective in limiting the spread of the virus, resulted in unprecedented negative economic welfare losses. The U.S. economy experienced its deepest decline since official record keeping in 1947, as GDP shrank by an annualized rate of 32.9% in the second quarter of 2020.[2] With the enforcement of the pandemic curbs, the hit to the labor market was unprecedented as well.[3] In April 2020, the unemployment rate rose to 14.8%, a figure that has never been recorded since the start of data collection in 1948.[4] To counteract the adverse economic fallout of the pandemic, the U.S. federal government put in place (March 2020), a stimulus package of about 2 trillion dollars; the so-called CARES act which is documented as the largest package in history (Bayer et al., 2020).

Given that knowledge on the effectiveness of the anti-contagion policies and the economic stimulus measures in the labor market is essential to timely plan effective short-run interventions, a large number of studies document the impact of these two policies in unemployment. Bayer et al. (2020) state, for the U.S., that in the period between mid-March and May 2020, more than 40 million initial unemployment claims were submitted as a result of the pandemic restrictions. Forsythe et al. (2020) document that firms in the U.S. reduced dramatically job vacancies from March 2020 onwards and, at the same time, there was a big spike in unemployment insurance claims. Bartik et al. (2020) by using a primary data set on small firms in U.S., find that compared to the respective magnitudes of January 2020, during the period of the pandemic a considerable number of firms temporarily closed part of their operations and lowered the number of employees. The causal effect of states' COVID-19 restrictive policies on the labor market is also discussed

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[1] See https://covid19.who.int/.
[2] See https://fred.stlouisfed.org/.
[3] For the effects of the pandemic on other markets, such as the sovereign bond market or the stock market, see Daehler et al. (2021) and Ftiti et al. (2021), respectively.
[4] See https://www.bls.gov/data/.

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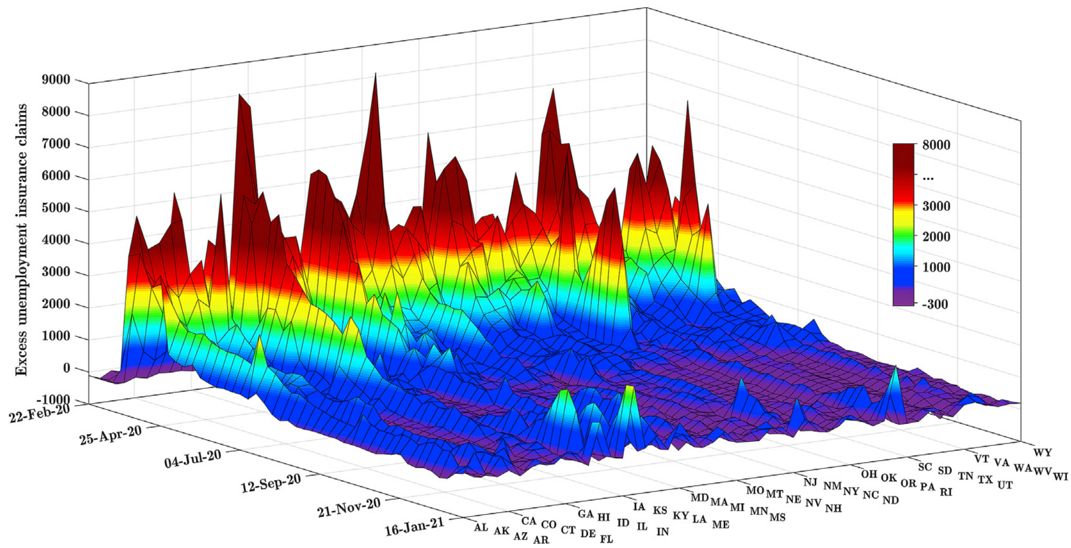

Fig. 1. EUC per state

Notes: EUC refers to the excess unemployment insurance claims. The two-digit state abbreviations are: Alabama: AL, Alaska: AK, Arizona: AZ, Arkansas: AR, California: CA, Colorado: CO, Connecticut: CT, Delaware: DE, Florida: FL, Georgia: GA, Hawaii: HI, Idaho: ID, Illinois: IL, Indiana: IN, Iowa: IA, Kansas: KS, Kentucky: KY, Louisiana: LA, Maine: ME, Maryland: MD, Massachusetts: MA, Michigan: MI, Minnesota: MN, Mississippi: MS, Missouri: MO, Montana: MT, Nebraska: NE, Nevada: NV, New Hampshire: NH, New Jersey: NJ, New Mexico: NM, New York: NY, North Carolina: NC, North Dakota: ND, Ohio: OH, Oklahoma: OK, Oregon: OR, Pennsylvania: PA, Rhode Island: RI, South Carolina: SC, South Dakota: SD, Tennessee: TN, Texas: TX, Utah: UT, Vermont: VT, Virginia: VA, Washington: WA, West Virginia: WV, Wisconsin: WI, Wyoming: WY.

in several other studies (Gupta et al., 2020; Rojas et al., 2020; Coibion et al., 2020).

Similarly, the role of economic stimulus, as enacted by the CARES act towards easing the effects of the pandemic, has attracted a lot of research attention. Bayer et al. (2020) find that the CARES act mitigated the output losses by 5 percentage points, while similarly Faria-e-Castro (2021) show that the generosity in unemployment benefits under the CARES act has contributed notably to raise output. Bhutta et al. (2020) show that, without the CARES act stimulus, nearly 50 percent of the households that entered in unemployment would have not been able to cover their basic expenses, whilst Altonji et al. (2020) and Boar and Mongey (2020) both find no evidence that the increased unemployment benefits act as anti-motive in returning to the job market at the same wage. The effectiveness of economic stimulus is also backed by the findings of other studies (Birinci et al., 2021; Gourinchas et al., 2021; Casado et al., 2020).

This paper empirically validates the current theoretical work on the second-wave SIR-macro type models. By conditioning on the state of the pandemic, we assess the impact of non-pharmaceutical interventions (NPIs) and economic support measures (ESM) on excess unemployment insurance claims. Using weekly data and by employing a Panel VAR (PVAR) model we reveal the following points. First, a shock in NPIs raises unemployment claims for up to six weeks. Second, ESM reduce unemployment but not instantaneously; the impact takes about three weeks to be felt on unemployment and lasts for at least 16 weeks. Nevertheless, ESM can only partially mitigate the negative impact of lockdowns on the labor market. Third, the deployment of ESM is not driven by the state of the pandemic per se, which arguably suggests that policymakers condition their economic support decisions more by looking at how the labor market reacts to the pandemic rather than the severity of the pandemic itself. Our findings arguably suggest that the economic cost of the pandemic might have been mitigated further if, economic stimulus was deployed at an earlier time.

The paper proceeds as follows: Sections 2 and 3, present the data and outline the methodology, respectively. Section 4 reports the findings and finally, Section 5 concludes.

2. Data and preliminary analysis

For all U.S. and over the period spanning from February 2020 (2/22/2020) to January 2021 (1/16/2021), we use weekly data on: i) the excess initial unemployment insurance claims per 100,000 of the weekly reported covered employment (EUC), ii) the non-pharmaceutical interventions (NPIs), iii) the economic support measures (ESM), and finally, iv) the weekly change of the confirmed COVID-19 cases per 100,000 inhabitants (CCC). Hence, our analysis involves four panel structured and strongly balanced variables. In more detail, excess unemployment claims refer to the difference between the weekly observed number of claims per 100,000 covered employment for the period of interest, and the mean value calculated by the respective weeks of the previous ten years (2010–2019). The raw data for the unemployment insurance claims and the covered employment come from the U.S. Department of Labor.[5] The constructed excess unemployment claims variable for all U.S. is illustrated in Fig. 1. Although it is relatively difficult to identify patterns at state-level, the 3D representation is useful in revealing the general evolution of the variables across all states and time.

NPIs and ESM across all U.S., on a daily basis, come from the Blavatnik School of Government (University of Oxford).[6] The former variable is constructed as the average of nine sub-indices (consist of containment, closure, and public information sub-indices), while the latter is created as the average of two economic response sub-indices.[7] Both variables are expressed as an index receiving values between 0 and 100. To match the time frequency of the two policy variables with the EUC, we average seven daily observations to a single weekly value. The index of the NPIs over time and across the U.S. states is shown in Fig. 2, while the index of the ESM, again over time and across all states, is presented in Fig. 3.

Moreover, we use data on the confirmed COVID-19 cases per 100,000

[5] see https://oui.doleta.gov/unemploy/claims.asp.

[6] See: https://www.bsg.ox.ac.uk/.

[7] See: https://www.bsg.ox.ac.uk/sites/default/files/2021-05/BSG-WP-2020-034-v3.pdf.

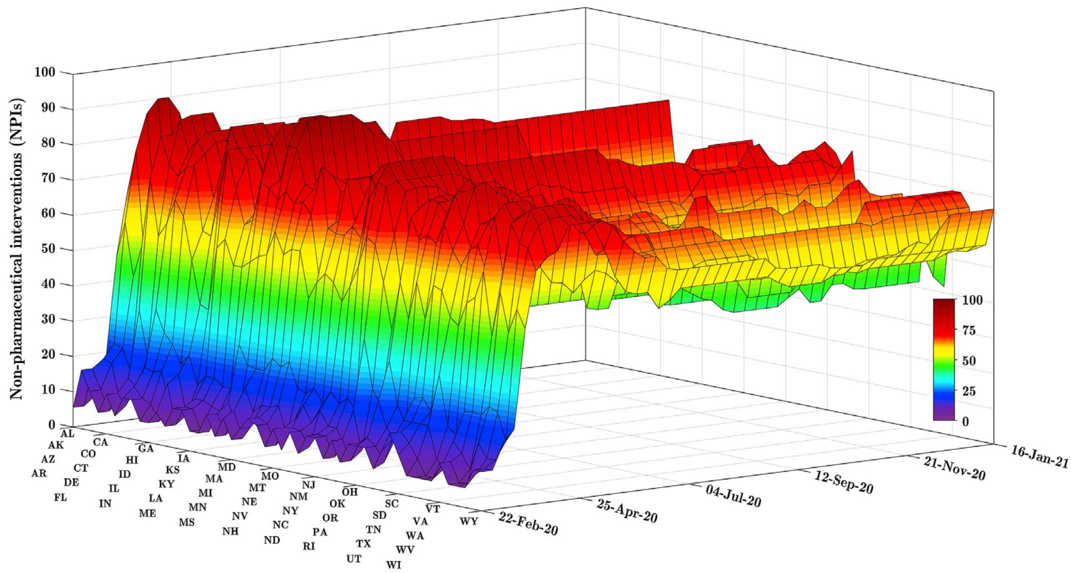

Fig. 2. NPIs per state

Notes: NPIs refers to the non-pharmaceutical interventions. The two-digit state abbreviations are: Alabama: AL, Alaska: AK, Arizona: AZ, Arkansas: AR, California: CA, Colorado: CO, Connecticut: CT, Delaware: DE, Florida: FL, Georgia: GA, Hawaii: HI, Idaho: ID, Illinois: IL, Indiana: IN, Iowa: IA, Kansas: KS, Kentucky: KY, Louisiana: LA, Maine: ME, Maryland: MD, Massachusetts: MA, Michigan: MI, Minnesota: MN, Mississippi: MS, Missouri: MO, Montana: MT, Nebraska: NE, Nevada: NV, New Hampshire: NH, New Jersey: NJ, New Mexico: NM, New York: NY, North Carolina: NC, North Dakota: ND, Ohio: OH, Oklahoma: OK, Oregon: OR, Pennsylvania: PA, Rhode Island: RI, South Carolina: SC, South Dakota: SD, Tennessee: TN, Texas: TX, Utah: UT, Vermont: VT, Virginia: VA, Washington: WA, West Virginia: WV, Wisconsin: WI, Wyoming: WY.

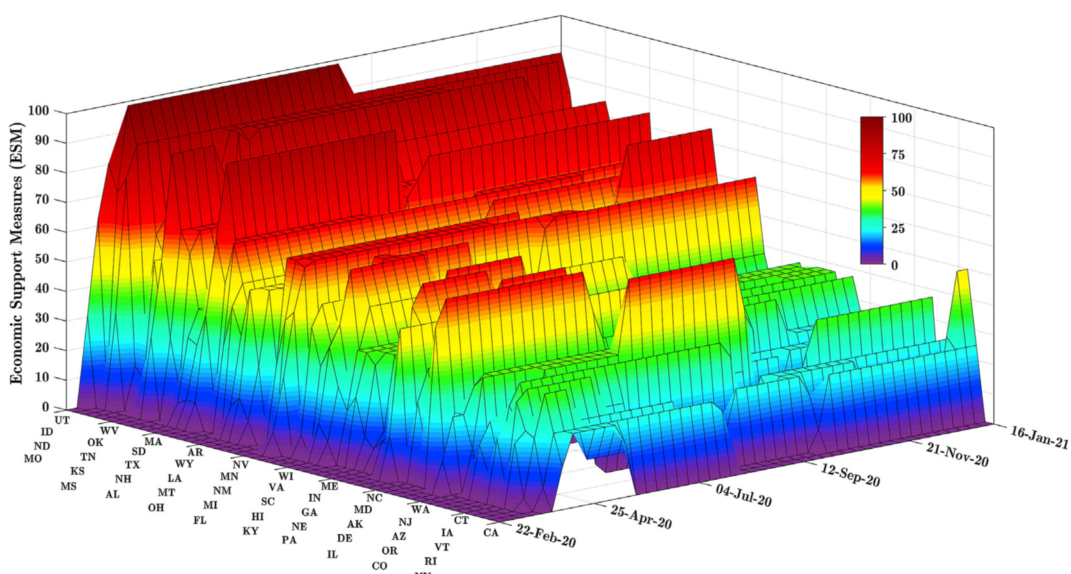

Fig. 3. ESM per state.

Notes: ESM refers to the economic support measures. The two-digit state abbreviations are: Alabama: AL, Alaska: AK, Arizona: AZ, Arkansas: AR, California: CA, Colorado: CO, Connecticut: CT, Delaware: DE, Florida: FL, Georgia: GA, Hawaii: HI, Idaho: ID, Illinois: IL, Indiana: IN, Iowa: IA, Kansas: KS, Kentucky: KY, Louisiana: LA, Maine: ME, Maryland: MD, Massachusetts: MA, Michigan: MI, Minnesota: MN, Mississippi: MS, Missouri: MO, Montana: MT, Nebraska: NE, Nevada: NV, New Hampshire: NH, New Jersey: NJ, New Mexico: NM, New York: NY, North Carolina: NC, North Dakota: ND, Ohio: OH, Oklahoma: OK, Oregon: OR, Pennsylvania: PA, Rhode Island: RI, South Carolina: SC, South Dakota: SD, Tennessee: TN, Texas: TX, Utah: UT, Vermont: VT, Virginia: VA, Washington: WA, West Virginia: WV, Wisconsin: WI, Wyoming: WY.

inhabitants. Source of this data set is the Centers for Disease Control and Prevention, while we use population estimates as of July 2019 by the U.S. Census Bureau to construct the confirmed COVID-19 cases per 100,000 inhabitants. The COVID-19 cases evolution is depicted in Fig. 4. Finally, Fig. 5, summarizes the mean values of all variables at state level.

We proceed to the preliminary analysis of the four variables by examining their order of integration (e.g., I(0) or I(1)). Thus, we execute a set of panel unit-root tests. We conduct the panel unit-root tests proposed by Levin et al. (2002), Harris and Tzavalis (1999), Breitung (2000), Im et al. (2003), and Pesaran (2003). The testing panel unit-root results are analytically presented in Table 1. From these results, we infer that all variables are I(0), at the conventional levels of significance.

3. Methodology

After the COVID-19 outbreak in early 2020, several studies develop

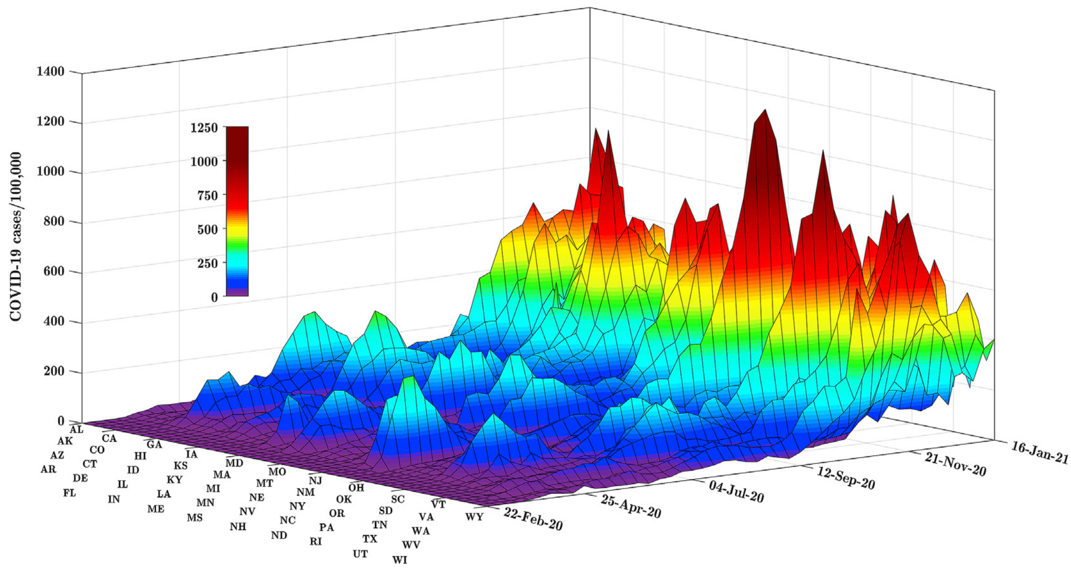

Fig. 4. COVID-19 cases per state.

Notes: COVID-19 cases refer to the confirmed COVID-19 cases per 100,000 inhabitants. The two-digit state abbreviations are: Alabama: AL, Alaska: AK, Arizona: AZ, Arkansas: AR, California: CA, Colorado: CO, Connecticut: CT, Delaware: DE, Florida: FL, Georgia: GA, Hawaii: HI, Idaho: ID, Illinois: IL, Indiana: IN, Iowa: IA, Kansas: KS, Kentucky: KY, Louisiana: LA, Maine: ME, Maryland: MD, Massachusetts: MA, Michigan: MI, Minnesota: MN, Mississippi: MS, Missouri: MO, Montana: MT, Nebraska: NE, Nevada: NV, New Hampshire: NH, New Jersey: NJ, New Mexico: NM, New York: NY, North Carolina: NC, North Dakota: ND, Ohio: OH, Oklahoma: OK, Oregon: OR, Pennsylvania: PA, Rhode Island: RI, South Carolina: SC, South Dakota: SD, Tennessee: TN, Texas: TX, Utah: UT, Vermont: VT, Virginia: VA, Washington: WA, West Virginia: WV, Wisconsin: WI, Wyoming: WY.

Fig. 5. Data sample mean values per state.

theoretical SIR-macro type models (a combination of Susceptible, Infected, and Recovered epidemiological models with macroeconomic models) to assess the impact of the pandemic on the economy (see, among others, Ansah et al., 2020; Baqaee and Farhi, 2020; Kaplan et al., 2020). In this study, we assess empirically the impact of the two major policies deployed during the pandemic, that is the NPIs and the economic support measures, on the labor market based on a typical fixed effects Panel VAR model. Given the existing work on the SIR-macro type models,

Table 1
Panel unit-root tests.

Variable Panel-test	EUC	NPIs	ESM	CCC
LLC	0.000 ***	0.000***	0.000***	0.000***
HT	0.000***	0.000***	0.000***	0.000***
BRE	0.000***	0.000***	0.007***	0.000***
IPS	0.000***	0.000***	0.000***	0.000***
PES	0.000***	0.000***	0.000***	0.000***

Notes: LLC, HT, BRE, IPS and PES refer to the tests of Levin et al. (2002), Harris and Tzavalis (1999), Breitung (2000), Im et al. (2003), Pesaran (2003), respectively. In all tests, the null hypothesis is that all panels contain unit roots. The symbol *** indicates the rejections of the null hypothesis at the 0.01 significance level, as this is indicated by the respective *p*-value. In the BRE test the lag structure for prewhitening is set equal to one, while the lag structure for the PES test is also set to one. Finally, in the PES test of the ESM variable a time trend is added.

our analysis is motivated by the theoretical underpinnings of Kaplan et al. (2020) and under this sense it consists an empirical validation of this type of theoretical models.

Kaplan et al. (2020) build a theoretical framework by integrating two distinct blocks, the epidemiological block (a modified SIR model) and the economic block (an adjusted New Keynesian model). Within this theoretical set-up, Kaplan et al. (2020) assess the impact of the pandemic and the resulting deployed governmental policies on the economic block of the model (e.g., in the labor market), by performing numerical experiments under three different scenarios. The first benchmark scenario assumes no government intervention. The second scenario incorporates a lockdown policy, without considering any type of economic stimulus, while the third scenario adds on top of the lockdown policy, economic support measures. Driven by the third simulation scenario of Kaplan et al. (2020) and the weekly frequency of our data set, the epidemiological block is modelled in our study by the change of the confirmed COVID-19 cases as an exogenous factor to the economic block, while the economic block is captured by the unemployment claims. Finally, the two policies (lockdown and economic stimulus) are proxied by the NPIs and the ESM indices, respectively.

Thus, we fit a third-order PVAR with panel-specific fixed effects to the data, as shown in Eq. (1):

$$\mathbf{y}_{i,t} = \mathbf{A}_1\mathbf{y}_{i,t-1} + \mathbf{A}_2\mathbf{y}_{i,t-2} + \mathbf{A}_3\mathbf{y}_{i,t-3} + \mathbf{F}_1\mathbf{z}_{i,t} + u_i + e_{i,t} \tag{1}$$

where state $i \in \{1,..,50\}$, week $t \in \{1,..,43\}$[8] for the period of interest (2/22/2020-1/16/2021), $\mathbf{y}_{i,t}$ is a (1×3) vector of endogenous variables; the NPIs, the EUC and the ESM. $\mathbf{z}_{i,t}$ is a (1×2) vector of exogenous variables; namely the one period lagged change of CCC and a time trend. $\mathbf{A}_1$, $\mathbf{A}_2$ and $\mathbf{A}_3$ are (3×3) coefficient matrices and $\mathbf{F}_1$ is a (2×3) coefficient matrix. Finally, u_i and $e_{i,t}$ are (1×3) vectors representing the state individual effect and the idiosyncratic error term, respectively. For both innovation terms, the standard assumptions hold. To recover the impact of the underlying structural shocks to our systems' variables, we rely on the Cholesky decomposition. In this instance, a meaningful identification of the underlying shocks depends on two critical assumptions. First, on the existence of an underlying recursive ordering, and second, on the appropriateness of the ordering.

The existence of a recursive ordering as well as its appropriateness, are validated based on the SIR-macro model of Kaplan et al. (2020). Hence, given the state of the pandemic as this is captured by the epidemiological block of the model, the government implements lockdowns to improve public health outcome. lockdowns affect the economic block of the model through two different channels: (i) economic activity slows down, as an upper utilization limit is imposed to the production function of the social sector, and (ii) the household labor supply is constrained. The resulting new equilibrium corresponds to a lower labor input. To mitigate economic welfare losses, the government reacts by introducing economic stimulus measures. This mechanism implies the following ordering in the $\mathbf{y}_{i,t}$ vector of endogenous variables: the NPIs enter first, followed by the EUC variable, succeeded by the ESM.

Moreover, in the presence of lagged dependent variables, parameter estimation under OLS is biased. Thus, we estimate the coefficient matrices by implementing the GMM estimation technique based on the forward orthogonal deviation transformation approach for instrumenting lagged variables. A final estimation related issue is raised by Lenza and Primiceri (2020), who point out that a mix of "regular" and "extreme" observations (e.g., data before and during the Covid-19 pandemic period), severely distorts parameter estimates in VAR type models. Our analysis covers only the very early pandemic data period, and thus heteroskedasticity is expected to cause milder consequences. To handle the issue of unequal error variances, we estimate Eq. (1) by specifying robust standard errors over different types of misspecification, such as heteroskedasticity. Overall, heteroskedasticity is not expected to affect our analysis in a way that significantly alters the conducted inference.

4. Results and discussion

Given the discussion in Section 3, we fit via the GMM estimation technique a third order PVAR with panel-specific fixed effects using a strongly balanced dataset and robust standard errors to account for different types of misspecification. The variables ordering is, NPIs, followed by EUC claims and ESM, while the one period lagged change of CCC and the time trend, both enter into the system as exogenous variables. The selected PVAR lag order is based on Hansen's (1982) *J*-statistic along with the three optimal moment and model selection criteria (MBIC, MAIC and MQIC) proposed by Andrews and Lu (2001). Specifically, by allowing a maximum lag order equals to four, the optimal lag structure is three. Moreover, the estimated PVAR meets the necessary stability condition given that all moduli of the respective eigenvalues are strictly less than one. The eigenvalue stability condition is illustrated in Fig. 6.

To derive the sixteen horizons ahead response of one endogenous variable to an impulse in another endogenous variable, we rely on Orthogonalized Impulse Response Functions, where the underlying shocks to the model are orthogonalized using the Cholesky decomposition. The response of the endogenous variables to an impulse on the exogenous variable is obtained by the estimates of the dynamic multiplier at each horizon. In our analysis the magnitude of all shocks is equal to one-standard deviation. Finally, the confidence bands presented, at the 60, 70, 80, 90 and 95 percent confidence levels, are estimated using a Gaussian approximation based on 1000 Monte Carlo draws from the

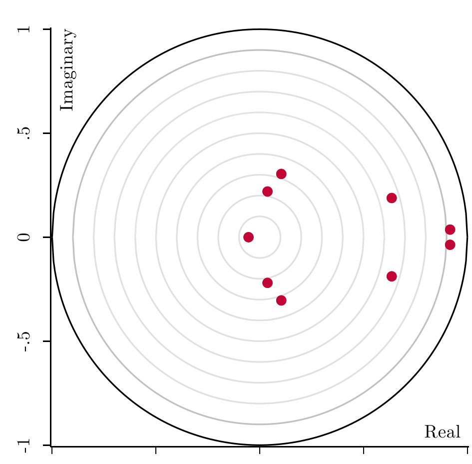

Fig. 6. Eigenvalue stability condition.

[8] 43 is the adjusted number of weeks after considering the lag structure of Eq. (1).

fitted specification. Fig. 7 shows how a shock to NPIs is transmitted to EUC. The trajectory path of the excess unemployment claims response is positive and statistically significant over the first six horizons (weeks). The effect of the shock reaches a peak after two horizons with excess unemployment claims to increase, on average per U.S. state, by 603 excess claims. The impulse response analysis shows that excess unemployment claims are quite sensitive to NPIs. In terms of trajectory's shape and duration, this empirical finding is consistent with the simulations of Kaplan et al. (2020), who show that lockdowns dramatically decrease labor input and hence unemployment claims increase. Similar are the results of Rojas et al. (2020) and Coibion et al. (2020), who find that local governments lockdowns and social distancing policies in the U.S., increased unemployment to historically unprecedented level. Finally, Forsythe et al. (2020), report that the U.S. labor market collapsed across all occupations with unemployment claims to illustrate a significant spike, over the COVID-19 pandemic period.

The average effect of government's stimulus policy on the U.S. labor market is illustrated in Fig. 8. In particular, the derived impulse response reveals that a stimulus shock has a negative effect on excess unemployment claims, especially over the longer horizons. The impact of the shock for the first three horizons is insignificant; it then remains negative and statistically significant across all horizons. The negative effect peaks after two and half months (ten weeks) with excess unemployment claims decreasing, on average per U.S. state, by 158 claims. Thus, the government's economic stimulus requires time to become effective (at least three weeks), and it can only partially mitigate the negative consequences of lockdowns in the labor market.

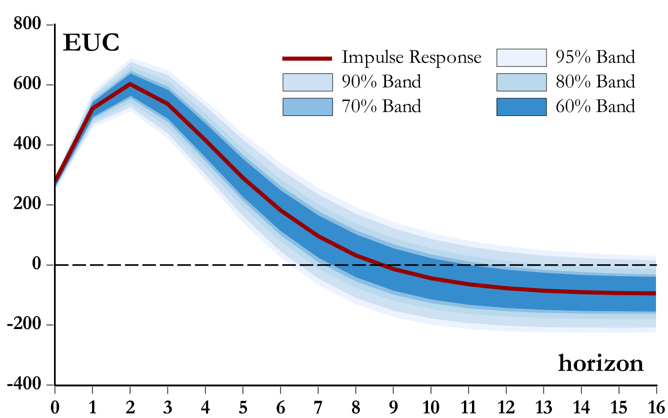

Fig. 7. EUC response to NPIs shock
Notes: EUC refers to the excess unemployment insurance claims and NPIs to the non-pharmaceutical interventions.

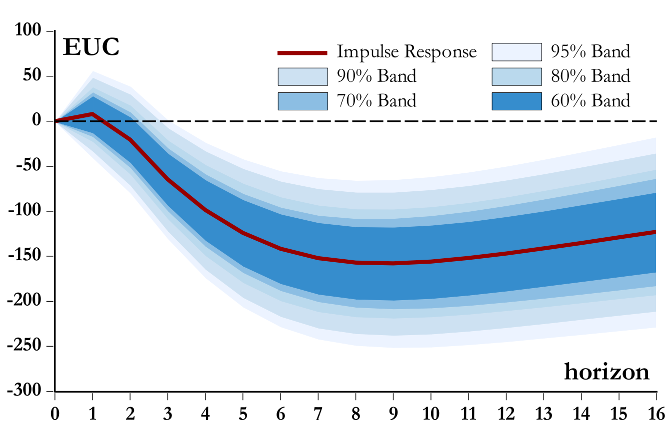

Fig. 8. EUC response to ESM shock
Notes: EUC refers to the excess unemployment insurance claims and ESM refers to the economic support measures.

Indeed, from Fig. 7, the cumulative impulse response reaction of excess unemployment claims to a one-standard deviation shock in the non-pharmaceutical interventions reaches a total of 2826 excess unemployment claims on average per U.S. state, after a period of six weeks. The linear impulse response analysis in Fig. 8 suggests that economic support measures would mitigate fully the above labor market losses (2826 excess unemployment claims on average per U.S. state) within the same period of six weeks if, and only if, a 6.4-standard deviation shock in economic support measures is realized. This underlines the enormous challenges economic support has been facing in order to counteract the adverse impact of non-pharmaceutical interventions on the labor market.

The effectiveness of the economic stimulus is consistent with Kaplan et al. (2020), who find that economic stimulus impacts substantially economic aggregates, with positive consequences on unemployment claims. Additionally, within an empirical framework, Casado et al. (2020) by using low frequency data over the COVID-19 period, focus on the impact of the economic support measures to the U.S. economy and find that the implemented stimulus contributes significantly to relieve the adverse outcomes in the labor market. Moreover, Chudik et al. (2021) by estimating a threshold-augmented Global VAR specification for 33 countries find that the COVID-19 economic stimulus is a key determinant in mitigating the effects of the pandemic. Finally, Gourinchas et al. (2021) develop a theoretical model to assess the effectives of the COVID-19 economic stimulus measures over their ability to suppress firm failures. By calibrating their model for 64 countries, find that economic measures put in place by governments succeeded to reduce on average the failure rate by 4.7%, compared to the scenario with no government support.

While drastic lockdowns lead to a severe cost in the labor market (Kaplan et al., 2020), this cost puts governments under enormous pressure to mitigate the negative consequences of the conducted anti-contagion policies through the introduction of economic stimulus measures (Gourinchas, 2020) and at the same time to relax, as soon as possible, the intensity of the anti-contagion measures (Harris, 2020). The validity of these two assertions is reinforced by the trajectory path of the system's estimated impulse response functions. The first assertion is validated by the impulse presented in Fig. 9, whereas the second one is validated by the impulse shown in Fig. 10.

In particular, Fig. 9 indicates that a shock on NPIs leads to the immediate introduction of economic support measures. Indeed, once the U.S. government implemented policies to protect public health, it also acted decisively within a short period of time by deploying a set of economic measures to support the labor market and thus, economic recovery (Clarida et al., 2021). But with the NPIs in effect, the government is put under pressure to stave off the negative burden in the labor market and the overall financial cost by easing the stringency of the deployed lockdown measures (Block et al., 2020). Thus, Fig. 10 reveals that

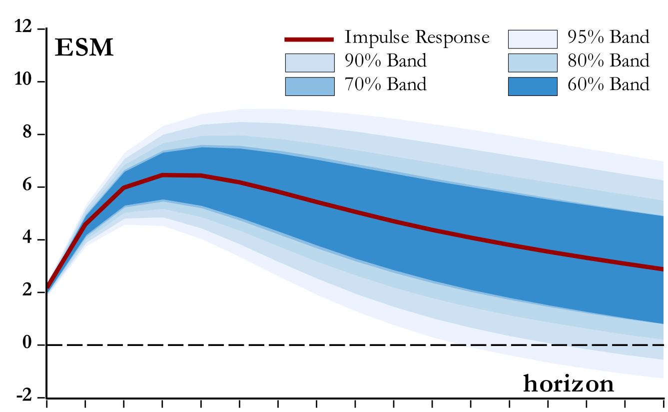

Fig. 9. ESM response to NPIs shock.

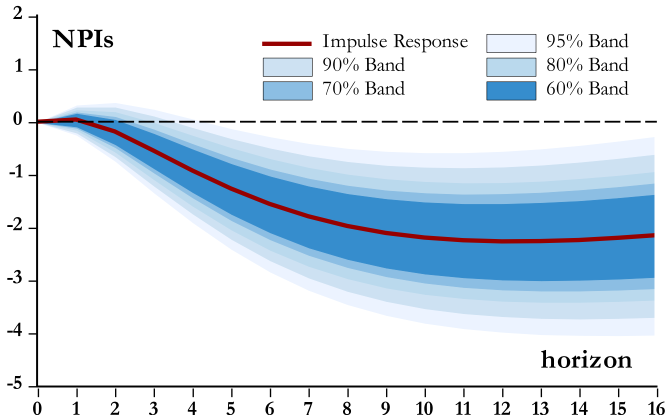

Fig. 10. NPIs response to ESM shock

Notes: NPIs refers to the non-pharmaceutical interventions and ESM refers to the economic support measures.

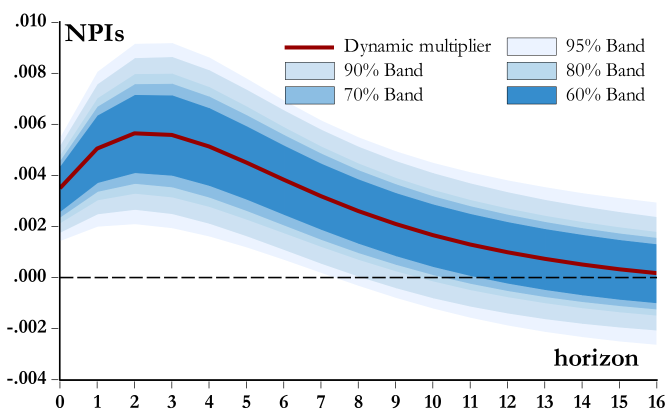

Fig. 11. NPIs response to CCC change

Notes: NPIs refers to the non-pharmaceutical interventions and CCC refers to the one period lagged COVID-19 confirmed cases per 100,000 inhabitants.

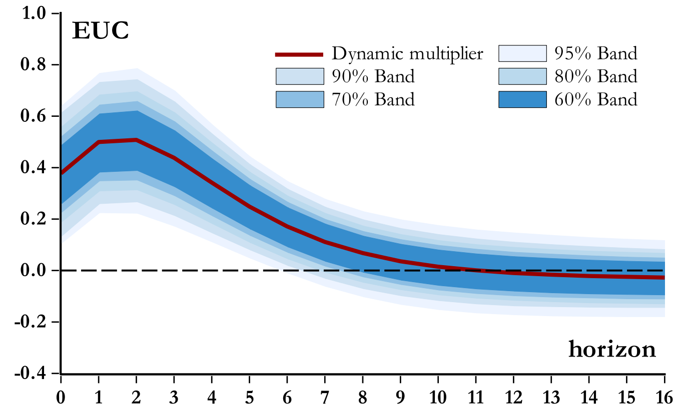

Fig. 12. EUC response to CCC change.

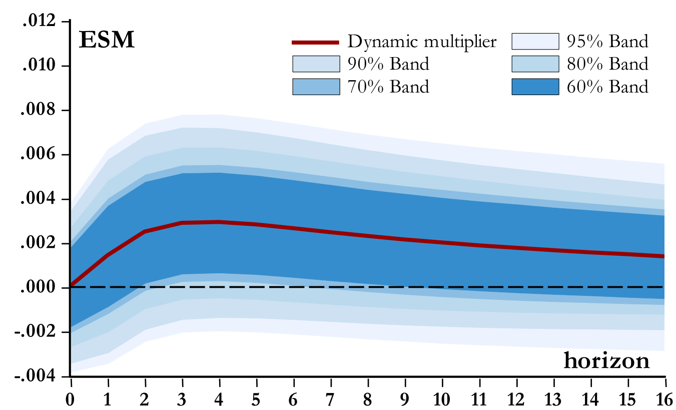

Fig. 13. ESM response to CCC change

Notes: EUC refers to the excess unemployment insurance claims, ESM refers to the economic support measures and CCC refers to the one period lagged COVID-19 confirmed cases per 100,000 inhabitants.

economic stimulus shock leads to a gradual relaxation of NPIs intensity, which turns to be significant only after a period of five weeks.

The effect of the pandemic (epidemiological block) on the system's main variables (economic block) is captured through the estimated dynamic multipliers, over the same horizons, and is presented in Fig. 11, **12** and **13**. Fig. 11 validates that the health-related restrictive measures are primarily driven by the state of the pandemic, as government seek to control the spread of the virus. The estimated dynamic multipliers shape a trajectory that is positive and significant over the first seven horizons following a unit change in the CCC variable. The revealed interaction between the pandemic and the resulted policies that cut back economic activity, constitutes a topic that has sparked an intense interdisciplinary research activity over the last two years and still grows. Characteristic examples of this direction are the studies of Eichenbaum et al. (2021), Baqaee and Farhi (2020) and Kaplan et al. (2020).

The direct effect of the pandemic on the labor market is depicted in Fig. 12. The estimated dynamic multipliers show that after a unit change in the CCC variable, the excess unemployment claims respond positively. This increase materializes over the first six horizons and the significant impact fades away for the remaining horizons. This finding is verified empirically, in a similar methodological framework, by Milani (2021). Finally, the deployment of economic support measures does not seem to be driven by the state of the pandemic per se (see Fig. 13). The respective dynamic multipliers show that a unit change in the CCC variable impacts economic support measures in a non-significant manner across all horizons which arguably suggests that policymakers condition their policy decisions more by looking at how the labor market reacts to the pandemic rather than the severity of the pandemic itself.

While governments are aiming to understand the complex mechanisms that drive the spread of the COVID-19 virus, our study empirically assesses the linkages between the pandemic, the deployed policies, and the labor market. From a theoretical perspective, our approach is validated within the framework of the SIR-macro type models, which permit the interaction between the current state of public health and the economy. In terms of policy implications, we find that stronger NPIs lead to higher measures of economic stimulus and that higher economic stimulus gradually leads to a relaxation of NPIs.[9]

Moreover, the two deployed policies (NPIs and ESM) appear to affect in opposite ways the labor market. The NPIs negatively influence the labor market by increasing substantially excess unemployment claims, while economic support measures can only partially mitigate the nega-

[9] The NPIs index does not consider how effectively these interventions are implemented in each U.S. state. To reflect this concern, we have modified the NPIs index by correcting it with community mobility data provided by Google (https://www.google.com/covid19/mobility/). The correction is based on the mobility trends data for two place categories, that is, workplaces and retail & recreation (restaurants, cafes, shopping centers etc.). The modified NPIs index exhibits a high degree of positive correlation (0.98) with the original one. The use of the modified index delivers qualitatively similar results to those reported in the paper.

tive consequences of lockdowns in the labor market.[10] These findings arguably suggest that the economic cost of the pandemic might have been mitigated further by better coordination of policy, if, for instance, both policies could have been synchronized better and, at the same time, economic support could have been more generous. The latter because, as noted above, a considerably large shock (a 6.4-standard deviations shock) in economic support measures would have been able to fully mitigate the adverse impact of non-pharmaceutical interventions. Notice, however, that Hao et al. (2022) find that sovereign credit risk has increased since the COVID-19 pandemic which makes it more challenging to borrow in international markets to finance more generous economic support for the labor market. In fact, as Daehler et al. (2021) note, sovereign spreads react to both economic and epidemiological news not least because a deteriorating epidemiological picture can lower confidence in the sovereign credit markets due to the prospects of prolonged lockdowns and a slower GDP growth recovery.[11]

Our work focuses on in-sample model estimates, whereas earlier studies provide out-of-sample analysis. Among these earlier studies, Aaronson et al. (2022) forecast, in an out-of-sample exercise, initial unemployment insurance claims in the U.S. with Google Trends (also noting that "unemployment" was the most searched term on Google in almost every county of the country). Additionally, Larson and Sinclair (2022) find that a model which exploits the variation in timing of state-of-emergency declarations, predicts U.S. initial unemployment insurance claims better than a model which incorporates Google Trends.

5. Conclusions

At the outbreak of the COVID-19 pandemic, governments were caught between the hammer and the anvil, as avoidance to enforce social distancing restrictions and lockdowns would have triggered an unparalleled death rate level, whereas the deployment of such policy measures would have pushed the economy towards profound decline. While in the early stages of the pandemic pure epidemiological models were employed to foresee how the virus evolves, this modelling approach proved unsatisfactory as the interconnection between the state of the pandemic and the economy was overlooked. As a result, a second wave of models that integrate the epidemiological block and the economic block to a unified framework have started to grow rapidly; the so-called SIR-macro models. This unified modelling framework is a valuable tool to governments, as now policy interventions to either block can be assessed over their total impact across both blocks. Thus, given the existing work on the SIR-macro type models this paper examines empirically the impact of the pandemic and the resulted governmental policies (NPIs and ESM) on the U.S. labor market.

We use weekly data between February 2020 and January 2021 for the 50 U.S. states and adopt a panel VAR empirical model to reach a number of findings. First, NPIs put upward pressure on unemployment claims instantaneously; the impact lasts for up to six weeks later. Second, the impact of ESM towards reducing unemployment is not felt immediately. Indeed, the impact takes about three weeks to be felt on unemployment and lasts for at least 16 weeks. Nevertheless, ESM only partially mitigates the negative impact of NPIs on the labor market. Third, the deployment of ESM is not driven by the state of the pandemic per se. This finding suggests that policymakers condition their economic policy decisions by paying attention to how the labor market reacts to the pandemic rather than the severity of the pandemic itself. This very finding also suggests that the economic cost of the pandemic might have been mitigated further by better coordination of the two COVID-19 related policies.

Moreover, our empirical outcomes reveal that there is an inescapable trade-off between government actions to protect public health and the resulting economic welfare losses. Under this trade-off, policymakers would certainly recognize the value of analyses that provide information over the effectiveness of their available policy tools and more importantly about the timing this effectiveness is felt. Towards this direction, our analysis reveals that once the U.S. government implemented policies to protect public health, it also acted decisively within a short period of time by deploying a set of economic stimulus measures to support the labor market and thus, economic recovery. But the revealed timing over the effectiveness of both policies, implies that the economic cost of the pandemic might have been mitigated further by better coordination of policy, if, economic stimulus had been deployed at an earlier time, as it takes about a month to become effective. Thus, both policies could have been synchronized better.

Overall, this paper focuses on the pandemic effects on the U.S. labor market prior to the full rollout of the U.S. vaccination programme. It is our intention to extend, in future work, our empirical model to assess the joint effects of NPIs and the different stages of the vaccination programme (in terms of the double dose and the so-called 'booster' one) on the U.S. labor market.

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Declaration of competing interest

None.

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[10] Although the estimated fixed effects Panel VAR specification does effectively capture, per equation of interest, the average impacts of the state-specific regressors (for instance, the non-pharmaceutical interventions and the economic support measures) on the outcome of the regressand (for instance, excess unemployment claims), these impacts cannot be assessed independently across each state. Thus, due to the model structure, the estimated effects of the regressors on the regressands represent the average effect.

[11] At this stage, it is worth mentioning that the conducted inference based on the empirical findings illustrated in Figs. 7–13, remain qualitatively unchanged once the CCC variable is incorporated within the VAR system as the first endogenous variable (instead of being pure exogenous).

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