The effects of voluntary social distancing and fiscal transfers on U.S. consumption and employment*

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Very preliminary, do not quote

Abstract

In this paper, we propose a new approach to assess the impact of voluntary social distancing and fiscal transfers consumption and employment in the United States over the first phase of the COVID-19 pandemic. To this end, using high-frequency data, we construct a novel measure of voluntary social distancing (VSD) that captures an individual's willingness to change their mobility to reduce the risk of infection. The evolution of our VSD measure over the course of 2020 supports the narrative that consumers adapted as the pandemic evolved. We find that increases in VSD reduce employment and consumption, but only the effect on employment is statistically significant. Increases in UI disbursements positively effect both consumption and employment and the absolute magnitude is significantly larger than the effects of VSD. This suggests that targeted transfers played a significant role in mitigating the effects of social distancing.

JEL Classification: E21,E24,E62

Keywords: COVID-19, consumption, employment, fiscal policy

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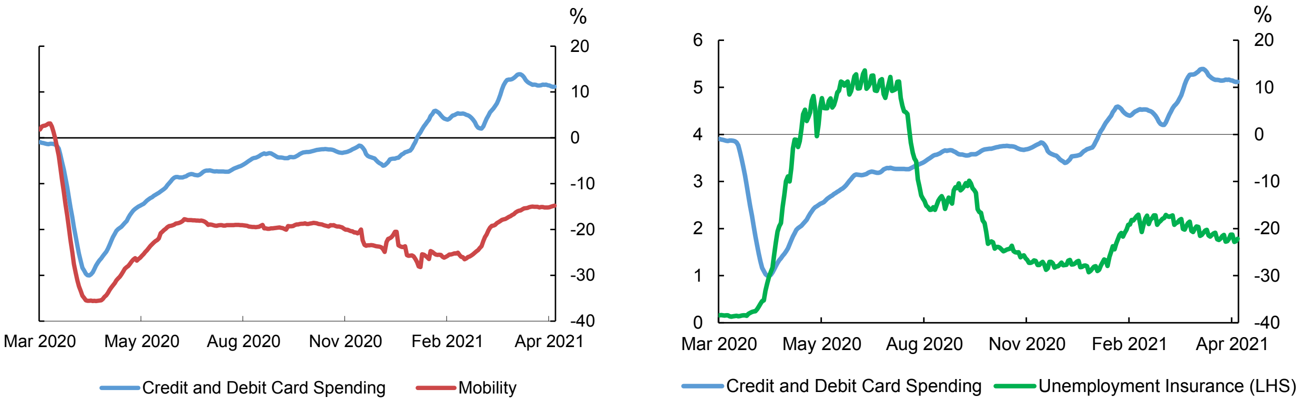
1 Introduction

Consumption and employment over the initial phase of pandemic have been driven by changes in mobility patterns and fiscal support provided to households. Left panel in Figure 1 shows how spending tracks changes in mobility patterns very closely. More specifically, the reduction in mobility patterns due to social distancing and lockdown measures negatively affected consumer spending and employment in the United States as households sought to reduce the risk of infection by COVID-19 and businesses were forced to close. On the other hand, massive fiscal support in the form of targeted and untargeted transfers to households contributed to partially offset these effects by stimulating demand. In particular, targeted unemployment insurance helped increase incomes above pre-pandemic levels and households reallocated spending to goods from inaccessible services. This is shown in the right panel of Figure 1.

Figure 1: Consumer spending, mobility and disbursments of UI benefits



Notes: Mobility and credit and debit card spending are deviations from January 2020. Unemployment insurance are daily disbursements in billions. Mobility is the average of five series produced from the Google Community Mobility reports: residential, workplace, transit, grocery and pharmacy, retail and recreation. All series are 14-day moving averages.

Government mandated restrictions and lockdowns played an important role in affecting economic activity but early literature suggests these measures have had less of an impact as compared to voluntary social distancing (VSD). Chetty et al. (2020) report that the state-ordered reopening of economies had small impacts on spending and employment and that fear of infection drove most of the change in consumer spending at the early stages of the pandemic. They compare credit card spending in comparable and neighboring states and use state reopening dates as an identification strategy to assess the effect of lockdown measures. Goolsbee and Syverson (2020) find that while consumer traffic fell by 60%, legal restrictions explain only 7 percentage points of that. Individual choices were far more important and seem tied to fears of infection. Cronin and Evans (2020) find that stay-at-home restrictions explain a modest fraction of the change in behavior and that private self-regulating behavior explain more than three quarters of the decline in foot traffic in most industries.

In this paper, we construct a measure of VSD for the United States and assess its impact along with unemployment insurance (UI) disbursements on consumption and employment over the pandemic period. Motivating this assessment is the long-term implications of pandemics and social distancing on the economy. Should employment impacts be larger from VSD or less mitigated by transfers, it would suggest more needs to be done to minimize the potentially scarring effects.

The structure of the paper is as follows. We lay out our empirical specification in Section 2 and a full description of the various data sources is given in Section 3. Results are presented and discussed in Section 4. Section 5 presents the results from a robustness analysis on our benchmark specification and Sector 6 concludes.

2 Empirical specification

There are three empirical exercises we conduct. In a first step, we develop a measure of VSD by purging standard mobility measures from the influence of government-mandated lockdowns. We estimate the following least squares regression for each U.S. state i:

$$mobility_{it} = c_i + \sum_{k=0}^{4} \beta_k OSI^i_{t-k} + \varepsilon^i_t \qquad \varepsilon^i_t \sim iid\mathcal{N}(0, \sigma^2_\varepsilon), \qquad t = 1, ..., T \tag{1}$$

$$VSD_t = \sum_{i=1}^{50} \omega_i \varepsilon^i_t \tag{2}$$

where $mobility_{it}$ is the inverted average of five mobility measures provided by Google, OSI_{it} is government-mandated lockdown measures captured by the Oxford Stringency Index, ε^i_t is the residual term and ω^i are 2019 population weights of each state i.[1] We use the population weighted residuals of

[1]We note that our mobility measure uses only 5 out of the 6 categories offered by Google. A discussion is presented in Section 3 where the data is presented and described. We also acknowledge that the OSI has been subject to some criticism. In particular, one criticism points to OSI reflecting the lockdown of the largest city in each State where the majority of economic activity takes place. Given that our end goal is to capture impacts on consumer spending, determined by economic activity, we don't believe this to be a major concern for our estimations. Finally, OSI is up to date the most comprehensive indicator of the true degree of legal lockdowns.

these regressions as our measure of voluntary social distancing as shown in eq.(2). We interpret these residuals as the purely voluntary behavioral component, a.k.a an individual's willingness, to change their mobility beyond what is mandated by the government restrictions.[2]

Second, we estimate different specifications of Local Projection (LP) models to assess the impact of our VSD measure and fiscal transfers on consumption and employment. This exercise aims to assess the relative importance of each of the shocks. Our benchmark specification consists of 3-variable LP model that includes voluntary social distancing or disbursement of UI benefits as the first variable and employment and spending as second and third. This allows us to analyze the differential impact of shocks to VSD and UI on employment and spending correspondingly. Furthermore, we analyze the impact of shocks to VSD and UI on high-income and low-income employment based on income levels in reference geographical zones. All variables are expressed in log levels and the choice of lags to be included is determined by the AIC criteria.

Third, we assess the time-varying impact of behavior regarding social distancing and fiscal transfers on consumption. This way, we assess how these relationships have changed over different stages of the pandemic. To this end, we estimate a time-varying parameters regression of spending on VSD and UI as follows:

$$C_t = c + \beta_t^1 VSD_t + \beta_t^2 UI_t + \epsilon_t \tag{3}$$

all variables are measured in differences and the time-varying parameters are modeled as random walks such that,

$$\beta_t^i = \beta_{t-1}^i + \eta_t, \qquad \eta_t \sim iid\mathcal{N}(0, \sigma_\eta^2), \qquad i = 1, 2 \tag{4}$$

To obtain estimates for the time varying parameters β_t and for the parameters in the model we first put the model given by eq.(3)-(4) in state space form. Then, we estimate a Gaussian linear state space system. The parameters in the system are estimated via maximum likelihood. We refer to Kim and Nelson (1999), chapters 2 and 3 for details on Kalman filtering techniques and maximum likelihood estimation of model coefficients.

[2]We refer to Section 5 for a robustness exercise where we add COVID-19 cases as an additional control in eq.(1). This way, we estimate the behavioural responses conditional on government lockdown measures and individual's knowledge of the spread of the virus.

3 Data

We draw on daily data from a number of different sources. The sample period under investigation goes from February 20th, 2020 until February 20th, 2021.

To measure aggregate consumption we use daily debit and credit spending transactions obtained from Opportunity Insights. This dataset aggregates and anonymizes individual data of transactions from a number of financial institutions. Opportunity Insights credit and debit card spending accounts for nearly 10% all U.S. debt and credit card transactions and is representative of around 76% of national personal consumption expenditures (PCE) as defined in the National Income and Product Accounts (NIPA) (Chetty et al., 2020). Over the period from February 2020 to March 2021, the correlation between credit and debit card spending and nominal PCE has exceeded 0.9.

Daily employment data are also drawn from Opportunity Insights database of employment from three private payroll service companies: Paychex, Intuit and Earnin. Chetty et al. (2020) show that employment rates derived from this data fall between the ranges implied by the nationally representative Current Employment Survey (CES, a representative survey of businesses) and the Current Population Survey (CPS, a representative survey of households) both produced by the U.S. Bureau of Labor Statistics (BLS). All Opportunity Insights data are provided in seasonality adjusted format.

To measure mobility, we use daily state-level mobility data provided by Google's COVID-19 community mobility reports. Mobility is expressed as percentage deviations from the level benchmark in January 2020, in the frequency of users' visits to six different locations: residential, workplace, grocery and pharmacy, retail and recreation, transit stations and parks. We do a simple average of five these locations, excluding parks, to compute our overall average mobility measure. Mobility at parks is excluded to avoid any potential seasonal effects underlying our data. Google mobility data is only available as of February 2020 and as such, cannot be subject to standard methods of seasonal adjustment. Therefore, by excluding parks from our analysis we exclude the component that is most subject to bias coming from seasonal factors. Also, parks mobility correlates very closely with weather, which is an indicator of the different seasons.

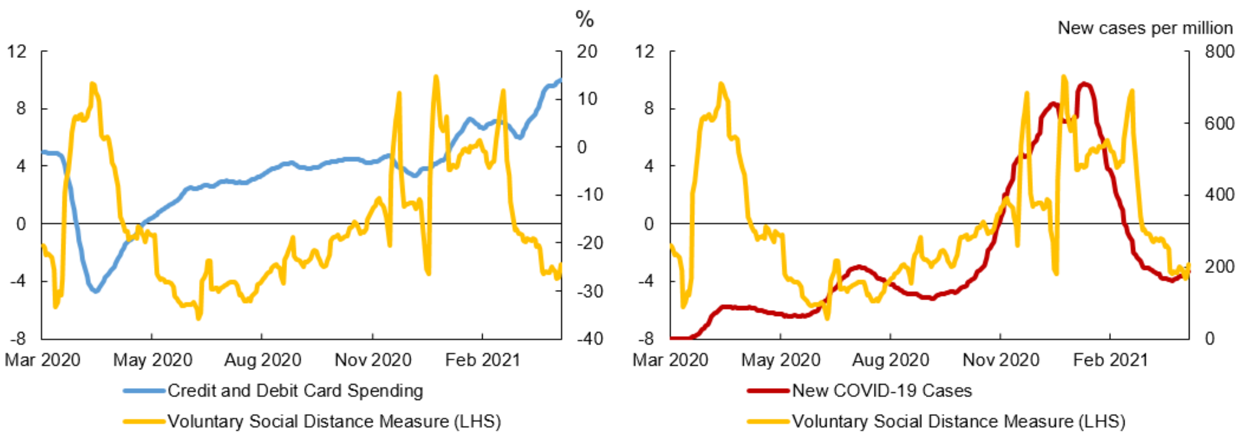
Finally, we use the Oxford Stringency Index (OSI) to measure legally binding containment and closure policies imposed across different states in the United States on a daily basis. The OSI is a categorical variable that summarizes publicly available information on indicators of governmental responses to control the spread of the virus. The OSI consists of an aggregation of 17 separate indicators that take on values between 1 and 100, with higher values reflecting more stringent measures.

4 Results

4.1 Voluntary social distance measure

Our measure of VSD closely tracks the changes in consumption and various waves of the virus, as shown in Figure 2. VSD rose substantially in the initial months of the pandemic but then sharply retrenched by early July 2020, consistent with the sharp decline and subsequent rapid rebound in output observed during that period. Thereafter, VSD gradually rose and peaked around the end of 2020 when cases reached their highest level but there was no sharp change in behavior as observed in the initial period of the pandemic. Since early 2021, VSD has declined sharply back to levels observed in July 2020 and consumption growth has risen steadily over that period.

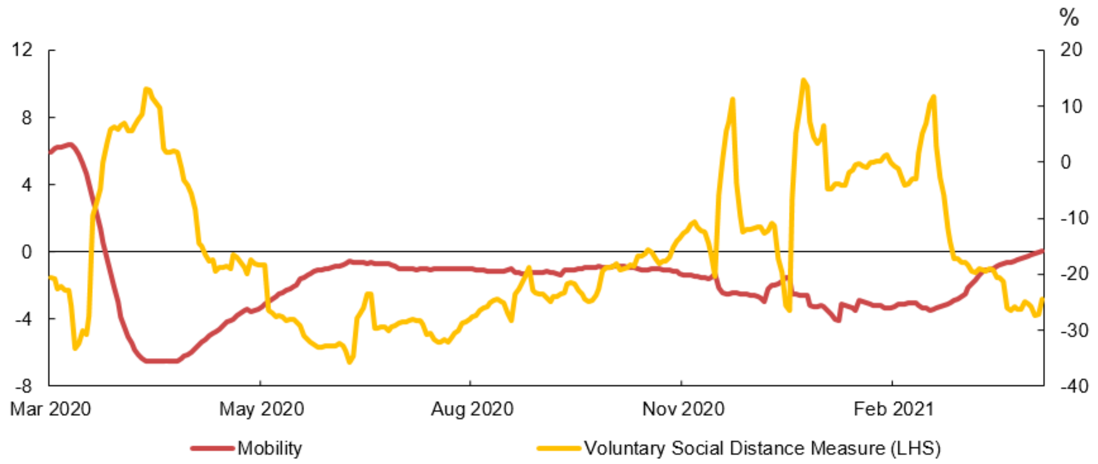
Figure 2: Voluntary social distancing, new COVID-19 cases and consumption



Notes: Credit and debit card spending and voluntary social distancing are expressed in deviations from January 2020. Higher values of VSD indicate more social distancing. New cases are evaluated per million and constructed using 14-day moving averages.

Compared to the standard measure of mobility that incorporates the effect of legal lockdown measures on behavior, shown in Figure 2, our measure of VSD suggests far less social distancing occurred during the second wave of the pandemic in the U.S. which took place during the summer of 2020 and more social distancing in the third wave, which took place during the fall and winter of 2020. This is consistent with the pattern of consumption over those waves – consumption was resilient in the second wave and moderated somewhat in the third wave. This highlights the importance of stripping out the effects of lockdown measures on mobility. For more than half of the states, lockdown measures proxied by changes in OSI explain only 40% of the total variation in mobility. Table A-1 in the appendix reports the R^2 values by state for eq.(1) depicting how much the OSI explains changes in mobility.

Figure 3: Voluntary social distancing and mobility



Notes: Credit and debit card spending and voluntary social distancing are expressed in deviations from January 2020. Higher values of VSD indicate more social distancing. New cases are evaluated per million and constructed using 14-day moving averages.

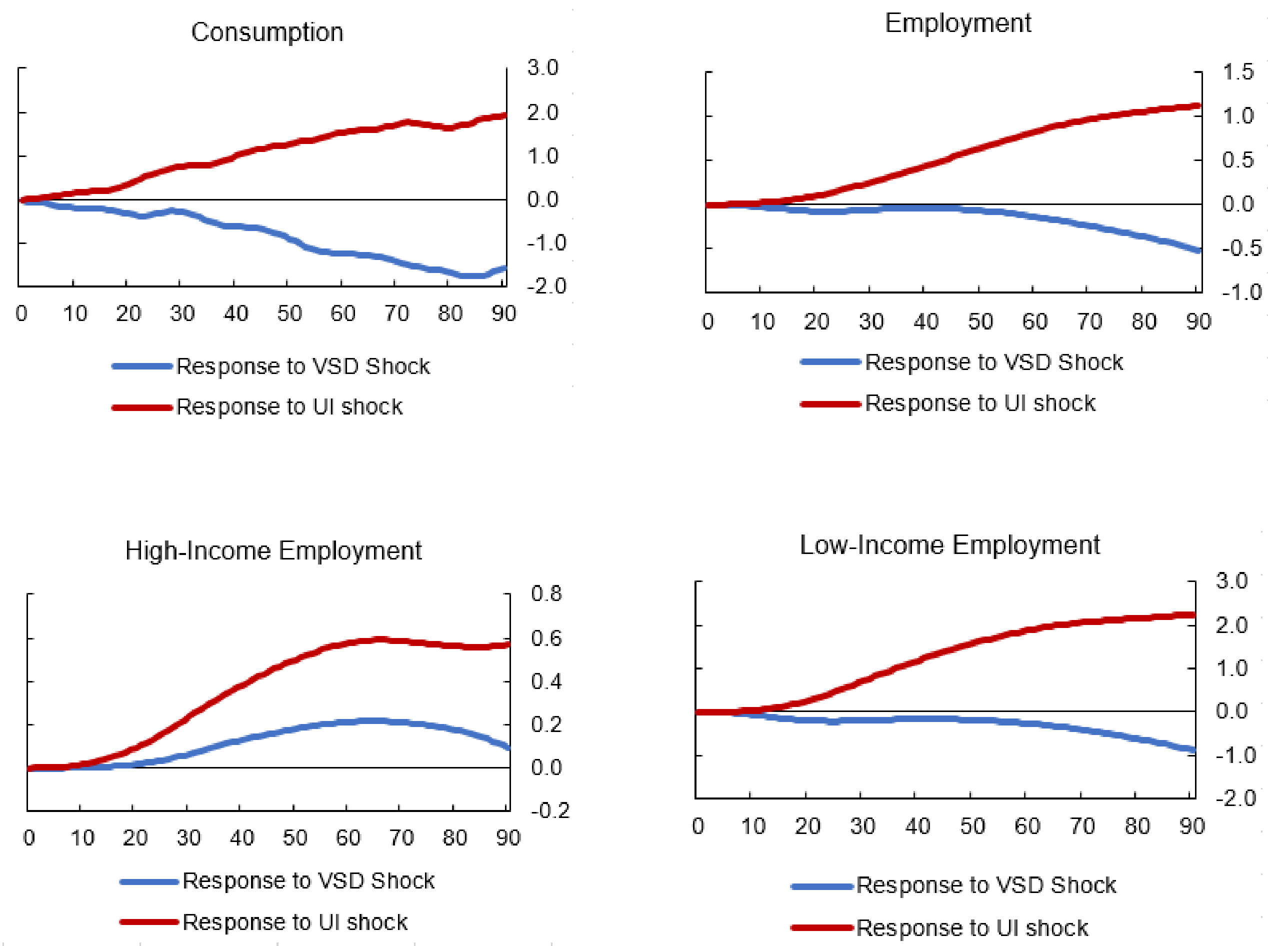
4.2 Local projections

In Figure 4, we observe that increases in our VSD measure seem to show a more persistent and statistically significant impact on employment than it does for consumption. Both employment and consumption decline in response to more VSD and while the magnitude of the consumption response is larger, it is not statistically significant. Alternative estimates using a restricted sample until [September] 2020 reveal a statistically significant impact on consumption to a VSD shock. This suggests that the behavioral adaptation of consumers and firms to the virus has increased as the pandemic progressed (Clarida, 2021). This is consistent with the relative resilience of consumption in the latter half of 2020 as compared to the beginning of the pandemic despite measured virus spread being much larger. The use of curbside pickup, deliveries, some services being offered virtually and online shopping are some of the ways consumers and firms adapted throughout the pandemic.

Stronger UI disbursements are associated with a positive and statistically significant impact on both consumption and employment. The impact of a fiscal transfer shock is larger than the impact from VSD shocks suggesting these were highly effective in mitigating the negative effects of the pandemic. For employment, the impact of a positive innovation to UI payments is more than 3 times as strong as a negative innovation to VSD after 90 days. For consumption, it is 1.2 times stronger. The strong employment response suggests UI spending is occurring in sectors where employment either was substantially weakened by the pandemic and therefore recovered as spending resumed or is being directed to new sectors, generating labour demand. We further disaggregate this response into low-income and high-income employment.[3]

[3] All our specifications consist of 3-variable LPs using VSD or UI as first variables and measures of employment and consumer spending as second and third variables, respectively. All charts with the cumulative impulse response functions and the corresponding confidence intervals are shown in the Appendix.

Figure 4: Impulse responses from local projections



Notes: Cumulative responses for 1 standard deviation shocks to VSD and UI over a 90 day horizon.

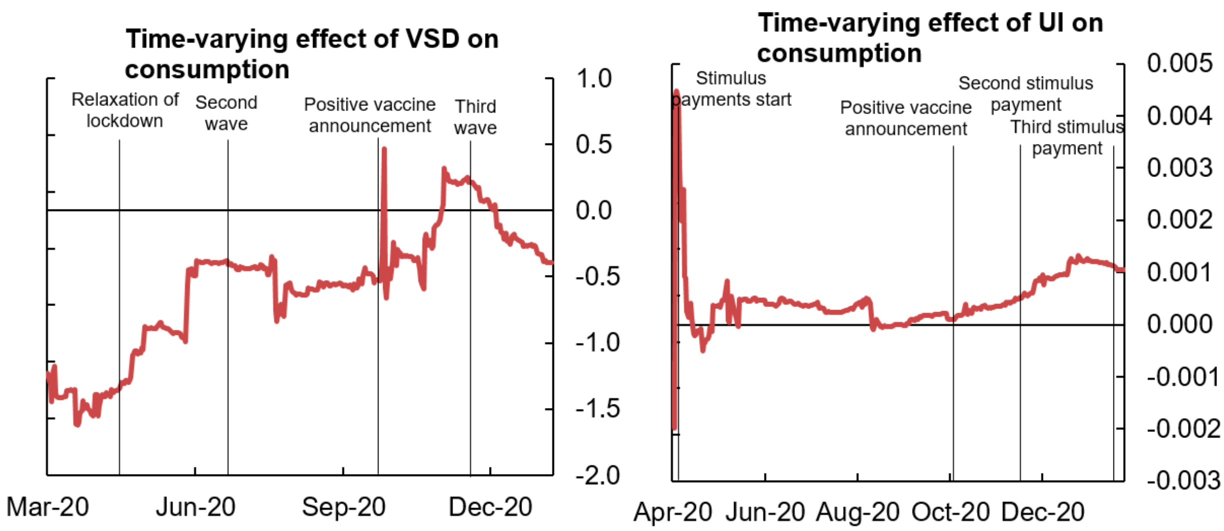
Employment in low income professions is much more responsive to VSD and UI shocks than high-income employment. In fact, we find that high-income employment positively responds to increases in VSD. All of these responses are highly significant. The pandemic significantly affected high-contact service sectors which employ a disproportionate number of low-wage workers but have largely left high-income workers unaffected given their ability to work remotely and where demand has remained relatively resilient. This is consistent with the findings of Chetty et al. (2020). The response to UI for low-income employment is almost 4 times as strong as high-income employment, providing some evidence that UI benefits are partly used to regenerate labour demand in affected sectors. For instance, it's possible that individuals receiving UI benefits may be using these benefits to purchase food from restaurants.

4.3 Time-varying regression

The estimated impact of our VSD measure on spending is observed to have diminished significantly throughout 2020 while the effect of UI has been positive and broadly stable over our sample period. This is shown in Figure 5. The negative effect of VSD on consumer spending shows large time variation over time as seen in left panel of Figure 5, even becoming positive briefly around November 2020. In this month, major announcements on vaccine related breakthroughs were made in the United States. The most negative impact observed, took place at the outbreak of the pandemic in March 2020. Gradually, over time, the impact turned less negative as people started to adapt to this pandemic regime and masking became increasingly a widespread practice. This took place despite increasing numbers of reported deaths due to COVID-19. This, therefore, provides further confirmation of a strong adaptation to living with the virus.

On the other hand, in the right panel of Figure 5, we observe that the estimated impact of UI on spending is positive and rather stable over time. Some larger variation is shown around periods when UI benefits rules underwent some type of change, i.e. UI lapsed during the fall of 2020 and were re-extended during the winter of 2020-2021.

Figure 5: Time-varying coefficients of VSD and UI on consumption



5 Robustness analysis controlling for COVID-19 new cases

The standard practice in the literature is to relate all behavioral changes in mobility to fear of the disease which is proxied by new COVID-19 case rates. To compare this to our approach to measuring behavior, we conduct a robustness check adding new COVID-19 case rates on our eq.(1). This way, we change the interpretation of our VSD measure as the residuals from eq.(5) represent now changes in behavior unrelated to new COVID-19 cases and whatever measure of fear toward the virus these might capture. Under this specification, our VSD measure should reflect issues such as fatigue caused by the large period of exposure to the virus and restrictions attached, and/or adaptation of behavior due to getting used to living with the disease and some normalization of daily routines due to the widespread use of precautionary measures such as wearing masks. These influences have been largely documented in reports, the media and existing literature (see Heimer et al., 2020; Meichtry et al., 2020; Clarida, 2021). Our extended residual regression is as follows:

$$mobility_{it} = c_i + \sum_{k=0}^{4} \beta_k OSI_{t-k}^i + \sum_{k=0}^{4} \alpha_k NC_{t-k}^i + \varepsilon_t^i \tag{5}$$

where NC_{it} is the share of new confirmed cases of COVID-19 over total population in each state i in the United States.

In Table A-1 we show the total share of variance explained by this regression, captured by the R^2, and by the regression in eq.(1). This way, we can explore if by the inclusion of new case rate in the mobility equation we can improve the amount of variation from our VSD measure that is captured. We note that the R^2 measure for the population weighted average for the U.S. aggregate series only increases from 0.46 to 0.58 when controlling for new COVID-19 cases. Also, from all 50 states shown in Table A-1, only 5 present an improvement in the R^2 measure that exceeds the 30%.

6 Conclusions

The main contribution of this note is the development of a single measure of VSD. The close association of our measure with consumption and the waves of new cases of the virus is in line with what one would expect given the observed consumption outcomes and widespread reports of social distancing fatigue.

The key finding of this note is that increases in VSD appear to negatively affect employment more than consumption and that the pandemic UI benefits were a highly effective mechanism to offset the negative effects of VSD. Perhaps the biggest surprise is that employment and not consumption is more affected by VSD implying that adaptation of households is strong.

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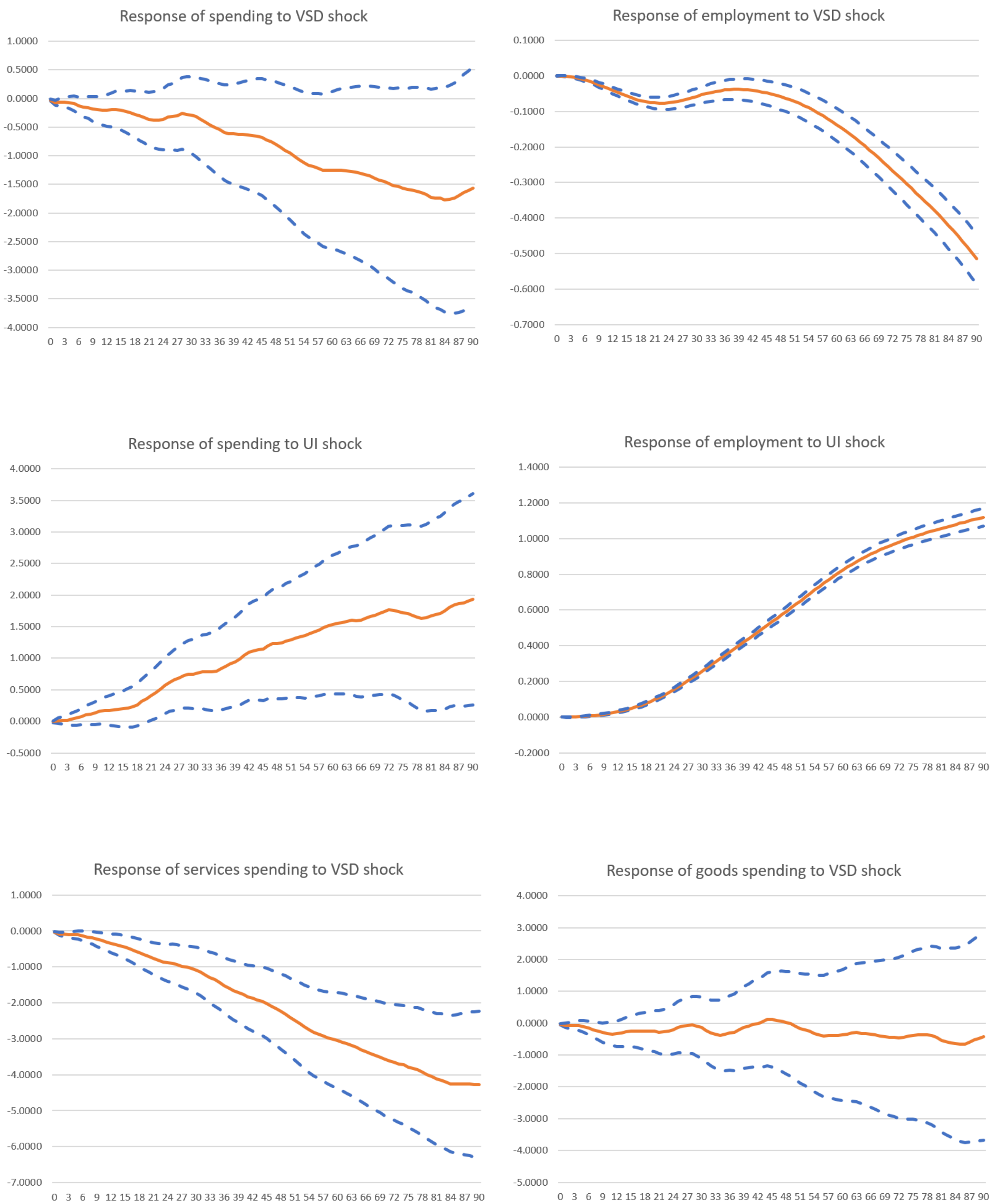
Appendix. Tables and Figures

Table A-1: Fit of OSI for changes in mobility by U.S. state.

State	R^2 no cases	R^2 with cases
Alabama	0.39	0.52
Alaska	0.44	0.69
Arizona	0.31	0.31
Arkansas	0.04	0.09
California	0.61	0.75
Colorado	0.40	0.71
Connecticut	0.49	0.69
Delaware	0.22	0.39
Florida	0.55	0.56
Georgia	0.23	0.23
Hawaii	0.10	0.24
Idaho	0.58	0.62
Illinois	0.54	0.62
Indiana	0.51	0.63
Iowa	0.26	0.30
Kansas	0.37	0.52
Kentucky	0.23	0.48
Louisiana	0.32	0.37
Maine	0.09	0.33
Maryland	0.59	0.62
Massachusetts	0.62	0.68
Michigan	0.68	0.70
Minnesota	0.47	0.51
Mississippi	0.19	0.16
Missouri	0.45	0.52
Montana	0.23	0.54
Nebraska	0.11	0.19
Nevada	0.67	0.74
New Hampshire	0.50	0.72
New Jersey	0.55	0.86
New Mexico	0.03	0.20
North Carolina	0.77	0.76
North Dakota	0.24	0.29
Ohio	0.25	0.49
Oklahoma	0.27	0.50
Oregon	0.30	0.50
Pennsylvania	0.43	0.61
Rhode Island	0.27	0.51
South Carolina	0.43	0.70
South Dakota	0.16	0.32
Tennessee	0.34	0.35
Texas	0.45	0.48
Utah	0.23	0.34
Vermont	0.73	0.81
Virginia	0.54	0.56
Washington	0.39	0.63
West Virginia	0.24	0.63
Wisconsin	0.63	0.73
Wyoming	0.29	0.58

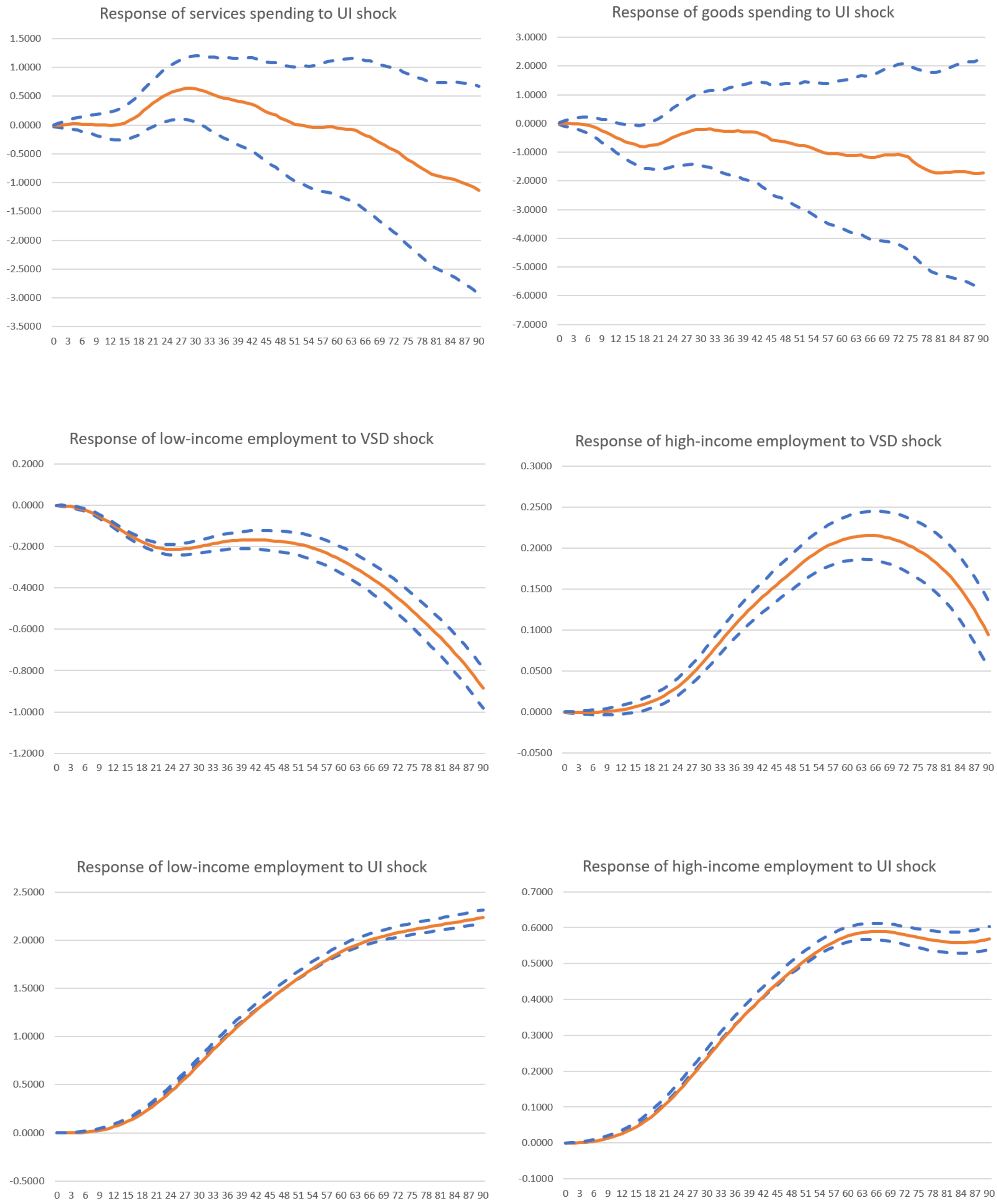
Notes: We report the adjusted R-square values from estimating eq.(1) by state. For population weighted U.S. wide values are: 0.46 and 0.58 respectively

Figure A-1: Impulse responses from local projections



Notes: Cumulative responses for 1 standard deviation shocks to VSD and UI over a 90 day horizon.

Figure A-1: Impulse responses from local projections (cont.)



Notes: Cumulative responses for 1 standard deviation shocks to VSD and UI over a 90 day horizon.