Why do households repay their debt in UK during the COVID-19 crisis?

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Why do households repay their debt in UK during the COVID-19 crisis?

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Abstract

This paper employs a vector autoregressive (VAR) model that nests neural networks and uses Mixed Data Sampling (MIDAS) techniques. We use data information related to COVID-19, financial markets, and household finances. In this paper, we investigate whether COVID-19 impacts household finances, like household debt repayments in the UK. Our results show that household debt repayments' response to the first principal component of COVID-19 shocks is negative, albeit of low magnitude. However, when we employ specific COVID-19 related data like vaccines and tests the responses are positive, insinuating the underlying dynamic complexities. Overall, confirmed deaths and hospitalisations negatively affect household debt repayments. We also report low persistence in household debt repayments. Generalized impulse response functions confirm the main results. As draconian measures, the lockdowns are eased it appears that the COVID-19 shocks are diminishing, and household financial data converge to the levels prior to the pandemic albeit with some lags. To the best of our knowledge, this is the first study that examines the impact of the pandemic on household debt repayments. Our findings show that policy response in the future should prioritise innovation of new vaccines and testing.

Keywords: COVID-19, household debt, ANN, VAR, MIDAS.

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1. Introduction

The paper sheds light on household financial behaviour to inform policy making response to the pandemic and the economic recovery. The starting point of our analysis is the report from the Bank of England (Money and Credit in April 2020) households have been repaying loans from banks while consumer credit has been dramatically fallen. Households repaid £7.4 billion of consumer credit, on net, in April 2020, the largest net repayment since the series began in UK. Higher payments towards household debt would enhance both household financial sustainability and financial resilience.

Understanding household's financial behaviour is of the utmost importance for the recovery from the pandemic. To do so, the paper employs a novel vector autoregressive (VAR) modelling using neural networks and Mixed Data Sampling (MIDAS) techniques. The lockdowns due to COVID-19 could have fundamentally shifted household behavior towards debt repayment as households opt for prudent management of their finances, whereas recent data also show an increase in households' savings.[1] The paper explores whether household debt repayment in the UK would persist, or it could be of transitory nature also considering the adverse economic conditions due to the pandemic. If higher household debt repayments were to last, would impact upon total indebtedness of the economy and financial stability.

Recent financial data showed that household debt repayments have been rather resilient during Covid-19 pandemic (OECD 2020, Bank of England 2020) while the importance of household finances is key to overcome the economic crisis that follows from the pandemic. Zabai (2020) and OECD (2020) show that household consumption is about 60 percent of GDP in OECD and household debt, mostly in the form of mortgages, captures up to 40 percent of banks' asset. Prior research Franklin et al. (2021) argue that many UK households have managed to weather the crisis of COVID-19, though authors also argue that households with unsecured loans could face financial difficulties. Georgarakos and Kenny (2022), using a new consumer expectations survey data for EU, show that policy makers by clearly communicating their COVID-19 interventions (see also Christelis, et al. 2020 for fiscal

[1] Lockdowns by reducing household spending could have affected debt repayments. Debt repayment moratoriums and stimulus packages to cope with COVID-19 could have played a role as they reduce household debt burdens. However, whether high household debt repayment would persist over time is open.

measures) would enhance consumers perception about the adequacy of these interventions and thereby they would incentivise household spending, including debt payment.[2] Kubota et al. (2021) employ a natural experiment in Japan to show that household would increase their spending as response to COVID-19 pandemic governments interventions that take the form of cash transfers (see also Chetty et al. 2020 for US; and Carvalho, et al. 2020 for UK).

The paper employs a unique Vector Autoregressive model that nests neural networks and incorporates financial markets data with COVID-19 related data and household financial data while controlling for government interventions. This model provides responses in household debt repayments to shocks due to COVID-19. Our model further examines the interconnectedness between household finances, financial markets, and COVID-19. Persistence in household debt repayment is particularly examined given changes in COVID-19 infections and government interventions. In some detail: First, we proceed with an in-depth statistical analysis of dynamics in financial markets in relation to COVID-19 and we also integrate in our analysis the household finances, like debt repayments. Second, we employ an innovative econometric analysis of VAR with Mixed Data Sampling (MIDAS) aimed at identifying and thereafter forecasting household debt repayment under different COVID-19 data. In addition, we address the issue of different frequency across variables as some are observable on a daily base, other on a monthly base. Third, we provide a detailed map of interconnectedness of the underlying causal nodes of various contributing factors to household finances as well as interactions between household debt repayment. Fourth, we rank the principal contributing factors to UK household financial behaviour so to inform policy makers to prioritise actions on specific factors. We also provide evidence, for comparison, across advanced countries like USA and Canada, to capture variability across countries. At the outset, our results show that household debt repayments' response to the first principal component COVID-19 shocks is negative, albeit of low magnitude. However, when we employ specific COVID-19 related data like vaccines and tests the responses are positive, insinuating the complexities of the underlying relationships. Overall, though, main

[2] Identifying consumer perceptions is beyond the scope of the current paper due to data availability issues but it is worth noting recent research of Roth and Wohlfart (2020) and Roth et al. (2021) that show most households in US underestimate the federal debt to GDP and once they are informed their perceptions change against raising government spending. This is of some significance as the COVID-19 crisis poses further challenges to governments interventions and fiscal imbalances.

COVID-19 data such as confirmed deaths and hospitalizations negatively affect household debt repayments. We also report low persistence in household debt repayments.

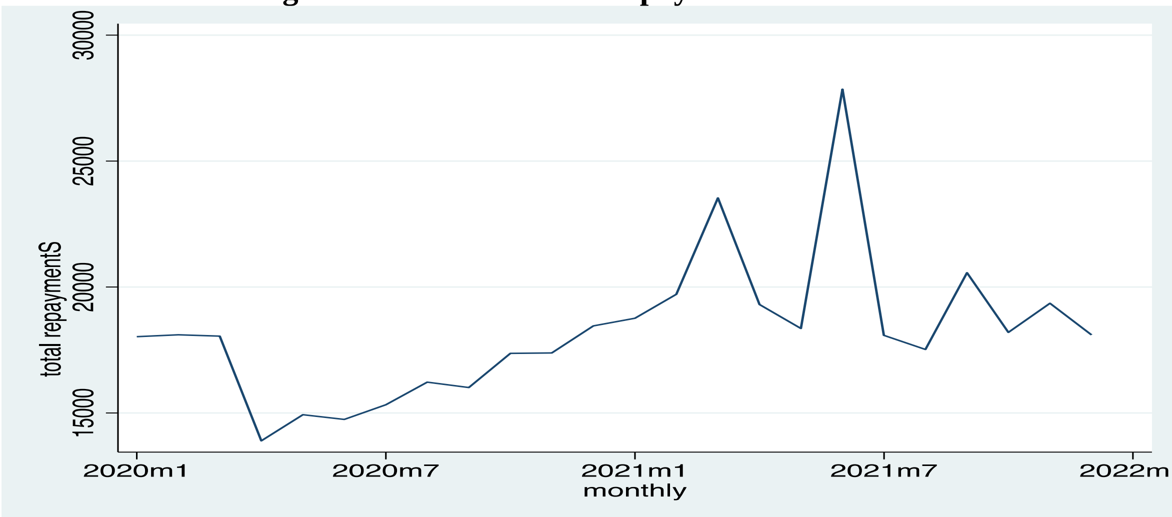
In what follows section 2 presents some stylised fact on the COVID-19 pandemic in UK in relation to household debt repayments. Section 3 presents the panel VAR model and the identification strategy while section 4 and 5 presents the data section and results respectively. The last section presents some concluding remarks.

2. COVID-19 pandemic in UK: some stylized facts

Undoubtedly, the COVID-19 pandemic has had detrimental effects on all aspects of economic and social life in the UK and world-wide. Based on an initial report from Bank of England (Money and Credit in April 2020) households were repaying loans from banks while consumer credit was dramatically fallen. Households repaid £7.4 billion of consumer credit, on net, in April 2020, the largest net repayment since the series began. Clearly higher payments towards household debt enhanced both household financial sustainability and financial resilience. Household debt repayments would also have implications for the financial industry and, financial stability.

Figure 1 shows total repayments of secured lending by individuals (in sterling millions) in the UK since the pandemic started in January 2020. There was a steady increase of household debt repayments since April 2020, reaching its pick in June 2021. In July 2021 there is notably drop and a fluctuation around 18,400 (in sterling millions) thereafter. From the Figure 1 one can infer the complexities involved in household debt repayments and its underlying dynamics. This paper is addressing these dynamics by fitting a panel VAR.

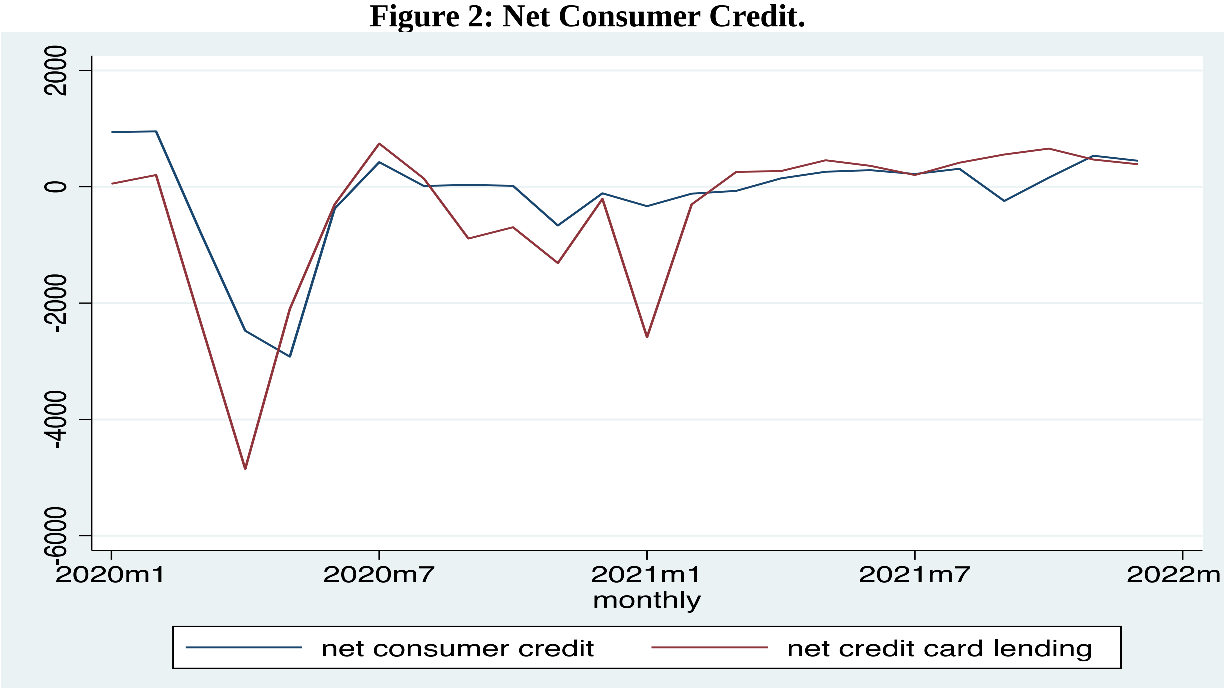
Figure 1: Household total repayments in the UK.



Source: Total repayments of secured lending by individuals (in sterling millions), Bank of England (Money and Credit).

Figure 2 shows the net consumer credit in UK. Both net consumer credit (excluding credit card) and net credit card lending to individuals (in sterling millions) dropped dramatically in the first six month of 2020 as the first lockdown was introduced. There was a recovery thereafter but there was a further dropped in the first quarter of 2021 as further lockdowns followed.

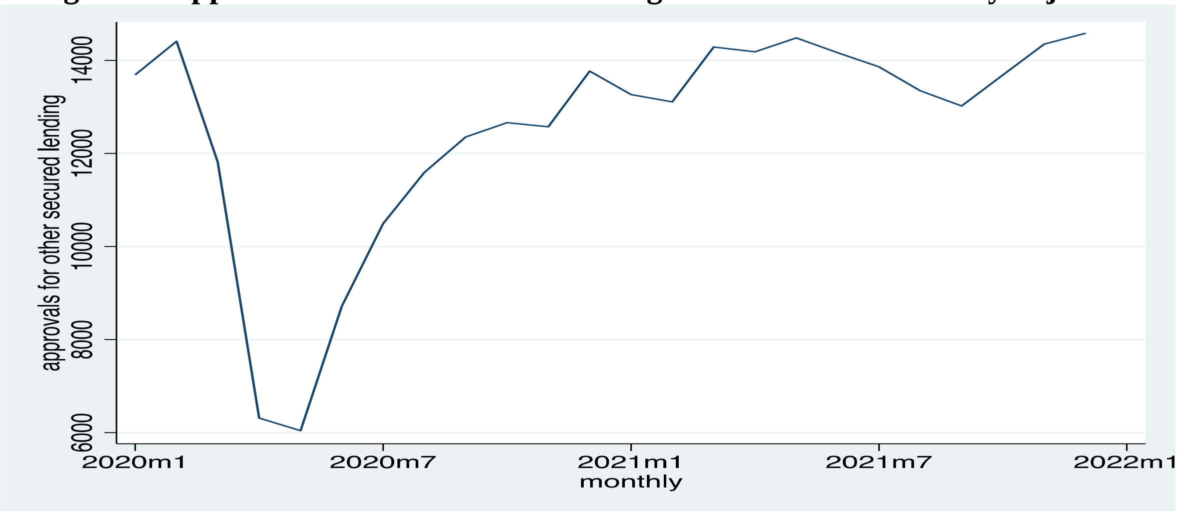
Figure 2: Net Consumer Credit.



Source: net consumer credit (excluding credit card) and net credit card lending to individuals (in sterling millions) seasonally adjusted, Bank of England (Money and Credit).

Figure 3 shows approvals for other secured lending to individuals seasonally adjusted in UK, showing a sharp drop in the first six in months in 2020 and a recovery thereafter but with some variability as further lockdowns followed.

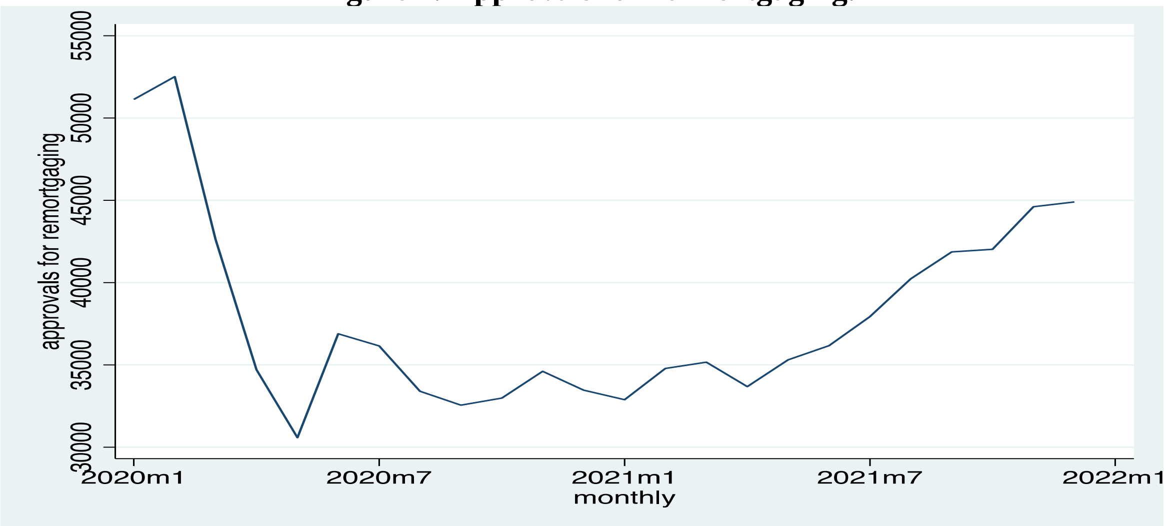
Figure 3: Approvals for other secured lending to individuals seasonally adjusted.



Source: Approvals for other secured lending to individuals seasonally adjusted (in sterling millions), Bank of England (Money and Credit).

Figure 4 shows approvals for re-mortgaging to individuals seasonally adjusted in UK, showing a very sharp and dramatic drop in the first six in months in 2020. The recovery thereafter was slow thereafter, while further lockdowns followed.

Figure 4: Approvals for re-mortgaging.



Source: Approvals for re-mortgaging (in sterling millions), Bank of England (Money and Credit).

A common pattern emerges from the above graphical analysis. Households' debt repayment and household credit increased and decreased respectively in the first six months of the pandemic and during the first lockdown, but ever since there are underlying dynamics that dominate while there is little persistence in either debt repayments or credit. To investigate these dynamics, we present next our panel VAR identification that account for COVID-19 infections and deaths as well as social and economic restrictions.

3. The impact of COVID-19 on household debt repayments: a VAR model identification.

The starting point of our analysis is to model the impact on COVID-19 on the economy. As financial markets react relatively quickly to COVID-19 and provide an information set of high frequency, on a daily base as the COBID-19 data, we opt for a simple model where a stock exchange market index, in our case the FTSE100 index of London Stock Exchange (LSE), is autoregressive as follows:

$$r_{i,t} = \alpha + \beta r_{i,t-1} + \delta_i C_{i,t} + \varepsilon_{i,t},\ \varepsilon_{i,t} \overset{iid}{\sim} \mathcal{N}_k(0, \sigma_\varepsilon^2) \qquad (1)$$

where $r_{i,t}$ is a $k \times 1$ vector of, for example, FTSE100 stock return for day i of period t,[3] β is an unknown autoregressive coefficient, α is a constant term $\varepsilon_{i,t}$ is an error term. COVID-19-related data (i.e., infections, deaths, hospitalisations) are noted as $C_{i,t}$. Moreover, δ_i $(k \times 1)$ contains unknown parameters COVID-19 related data, such as confirmed infections, confirmed deaths and hospitalisations. These parameters vary with the day (i) to capture the daily effect of COVID-19-related data $C_{i,t}$ $(k \times 1)$ on financial markets in an otherwise standard autoregressive model.

[3] In addition, we control for CAPEX-to-assets ratio and 12-month asset growth, book-to-market, earnings-to-price, cash flow-to-price, forward earnings-to-price, EBITDA-to-enterprise value, as well as dividend yield.

To focus on COVID-19 effects or extreme shocks, more generally, we also need a model for household finances, i.e., household debt repayments. So, next we model household debt repayments within a vector autoregression (VAR) as follows:

$$\underset{(m\times 1)}{\mathrm{y}_t} = \underset{m\times 1}{\mu} + \underset{0,(m\times m)}{B} y_{t-1} + \Gamma_{0,(m\times s_t)}\mathrm{r}_t + \underset{(m\times 1)}{\mathrm{u}_t},$$
$$\mathrm{u}_t \sim \mathcal{N}_m(0,\Sigma), t = 1,\dots,T, \qquad (2)$$

where μ is a vector of constant terms, matrix B contains unknown coefficients, Σ is an unknown covariance matrix, y_t contains information on m household financial data such as debt repayments, net lending etc. which we shall address more specifically in equation (3) below and, finally, r_t is a vector that contains all $r_{i,t}$ for a given t whose dimensionality is $s_t \times 1$, Γ contains unknown coefficients.

The problem is that in (2) we do not explicitly deal with COVID-19-related information, as it relates household debt repayments to financial markets. The channel of effects from COVID-19 to household debt repayments is implicitly through financial markets. However, given (1) and (2), we could relate financial-markets oriented information as in (1) to address how COVID-19 are reshaping the paradigm of household debt repayments using the following VAR:

$$\underset{(m\times 1)}{\mathrm{y}_{jt}} = \underset{(m\times 1)}{\mu_j} + \underset{0,(m\times m)}{B} y_{j,t-1} + \Gamma_{0,(m\times s_t)}\mathrm{r}_t + \underset{(m\times k)}{\delta_j} C_{i,t\,(k\times 1)}$$
$$+ \underset{(m\times m)}{B}(y_{j,t-1};\theta_B)\mathrm{y}_{j,t-1} + \underset{(m\times k)}{\Gamma}\left(\underset{(m\times 1)}{\delta_j, C_{i,t}};\theta_\Gamma\right)C_{i,t} + \underset{(m\times 1)}{\mathrm{u}_{jt}},$$

$$u_{jt} \sim \mathcal{N}_m(0,\Omega), t = 1,\dots,T, j = 1,\dots,n, \qquad (3)$$

where y_{jt} contains key variables for household finances in country j (for the purpose of this paper we select three countries: UK, USA, and Canada) and time t, μ_j are household-specific effects. δ_j is an $m \times k$ matrix of exposures to COVID-19 and the presence of i

and t indices implies that we have variables at different frequencies necessitating an application of mixed date sampling. The elements of matrices B, Γ in (3) are neural networks, and Ω is a covariance matrix. $\theta_{B_{ij,g}}$ and $\theta_{\Gamma_{ij,g}}$ are unknown parameters.

In detail, one issue with our datasets is that they come in different frequencies (some are observable on a daily base, other on a monthly base). We shall address the issue of different frequency across variables by using Mixed Data Sampling (MIDAS) (see Ghysels, et al. 2004, 2006, 2009). To this end, we fit all information into a vector autoregression (VAR) in Equation (3) with μ a vector of constant terms, B_0 a matrix containing unknown coefficients, and Σ the unknown covariance matrix. From the VAR we estimate how exposure coefficients δ of COVID-19, like confirmed infections, confirmed deaths hospitalisations, vary on their impact on household finances, like debt repayments, net lending. This model treats COVID-19 as a forcing variable and not as an exogenous shock since VARs are more appropriate for normal times but not when an extreme persistent shock takes place as in the case with COVID-19.

To estimate the model's parameters, we employ neural networks. It is well known that neural networks can approximate well any functional form to arbitrary accuracy. All available information of household finances would form part of the neural network equations so that generalized impulse response in the functions can be computed separately.

Thus, the neural network defines $\mathrm{B} = [\beta_{ij}]$, $\Gamma = [\gamma_{ij}]$, and we have:

$$\beta_{ij} = \sum_{g=1}^{G} \theta_{B_{ij,g}}\, \varphi(y_{t-1}),$$

$$\gamma_{ij} = \sum_{g=1}^{G} \theta_{\Gamma_{ij,g}} \varphi(\delta_j), \tag{4}$$

where $\theta_{B_{ij,g}}$ and $\theta_{\Gamma_{ij,g}}$ are unknown parameters, G is the number of nodes in the neural network, and the link function is $\varphi(z) = \frac{1}{1+e^{-z}}$, for all real numbers z. In detail, G denotes the order of the Artificial Neural Network (ANN) which we choose empirically based on the BIC. The model is estimated through standard Markov Chain Monte Carlo (MCMC) techniques for Bayesian inference.

It is well known that neural networks can approximate well any functional form to arbitrary accuracy (Hornik et al., 1989, White, 1989). Moreover θ_B and θ_Γ contain unknown parameters related to neural networks. So, in (3), there are, effectively, linear terms in $\mathbf{y}_{j,t-1}$ and $C_{i,t}$ augmented by nonlinear terms which serve two purposes. First, to relate higher to lower frequency data and, second, to consider the criticism of Oh and Patton (2021) that any linear model can be converted into a better model by making its coefficients dependent on a dynamic state variable to account for possible misspecification.

The VAR in (3) has data in different frequencies so, we estimate jointly (2) and (3) with a Mixed Data Sampling (MIDAS)- like approach (or alternatives) under the assumption:

$$vec(\delta_j) \sim \mathcal{N}_k(0, \sigma_\delta^2 I_{km}), j = 1, \ldots, km, \tag{5}$$

where I_{km} is the identity matrix, and σ_δ^2 is a scale parameter.

In fact, the model in (1) and (3) allows for a treatment of data in different frequencies through the prior in (4) rather than a MIDAS approach which, despite its benefits, comes at a cost of specifying functional forms for the dependence of lower to higher frequency data. Of course, (4) is not innocent either but it allows a parsimonious representation. Other than (4), all priors for location parameters are flat and the same is true for covariance matrices and scape parameters (e.g., Zellner, 1971, pp. 53 and 225).

The focus on household's debt repayments is justified because: First, households rely on funds and liquidity as well as their resilience and recovery in the aftermath of an extreme event/shock is key for the economic recovery. Second, we relate financial market to household debt repayments to address how extreme events/shocks are reshaping the paradigm of household debt. One implication is that through $\gamma_{ij} = \sum_{g=1}^{G} \theta_{\Gamma_{ij,g}} \varphi(\delta_j)$, in Equation (4) we can approximate daily responses of household-finances to COVID-19-related variables even though household finance variables are not available daily.

In summary, the steps for our estimations are as follows: first, we perform historical simulations to examine model fit; second, given different scenarios for COVID-19 as well as different government interventions we estimate the impact on household financial data like debt repayments in the VAR using generalized impulse response functions; the focus is on how financial markets, as well as government interventions like lockdown, lifting lockdown and government financial assistance would affect household debt repayment in 2020, 2021 and 2022. We shall also provide simulations for future paths of household debt payments and household financial resilience based on different scenarios that would also control for new health developments such as test and trace applications, drag and vaccine discovery.

4. The data set.

4.1 Household debt repayments and COVID-19.

We draw on three data sources. The non-pharmaceutical interventions (NPI) data is from the Oxford COVID-19 Government Response Tracker (OxCGRT) (Hale et al., 2021) while the daily COVID-19 case data are from the Johns Hopkins University's Center for Civic Impact. OxCGRT collects publicly available information on 19 indicators of government responses related to containment and closure policies, economic policies, and health system policies, which are combined into four indices ranging from 0 to 100. The indices include the number and strictness of government policies and do not indicate appropriateness or effectiveness.

Data on government interventions concern three main areas of interventions: a) containment and closure, b) health system, and c) economic stimulus. All the indicators are available on a daily and monthly basis. The containment and closure interventions include eight sub-indicators: i) school closing, ii) workplace closing, iii) cancellation of public events, iv) restrictions on gatherings size, v) public transport closed, vi) stay at home requirements, vii) restrictions on internal movement, and viii) restrictions on international travel. The second area of interventions include health system: i) public information campaigns, ii) testing policy, and iii) contact tracing. Since these policies help to cope with the pandemic quicker, they may be also discounted in stock prices. The third area includes economic stimulus packages such as: income support, and debt or contract relief for households. These stimuluses affect the economy through various channels. For instance, stimulus supports consumption and spending in times of distress; hence, they may significantly affect local equity markets. Finally, besides the individual measures, we also consider the overall Stringency Index by Hale et al. (2021). The index aggregates the data pertaining is re-scaled to create a score between 0 and 100. This index provides a synthetic measure of the intensity of different non-medical government interventions during the pandemic. Table 1 reports the main descriptive statistics of our sample.

Regarding the data set: primarily, our focus is on the UK economy, and we collect data from various sources that we have been already granted access to. Our data sources include the Household Finance Review of UK Finance, the Money and Credit statistics of the Bank of England, the Business Impact of COVID-19 Survey (BICS) of ONS, as well as the Management and Expectations Survey. The paper also focuses on international comparisons and employs data for USA and Canada from the Statistical Offices of the USA and Canada. In terms of COVID-19 related data, we measure exposure to the pandemic by computing the growth rate of the cumulative number of confirmed cases (and deaths) in each country on a daily frequency (see Table 1 for COVID-19). The frequency of these data is daily and includes the following variables: vaccines; tests; confirmed deaths; hospitalisations; school closing; workplace closing; cancel events; gatherings restrictions; transport closing; stay home restrictions; internal movement restrictions; international movement restrictions; information campaigns; testing policy; contact tracing; stringency index. All the changes in government policies are tracked daily and monthly. Therefore, when we perform the regressions based on weekly returns, we calculate the weekly averages for the considered period.

Table 1: COVID-19 related data.

	Mean	Std. DEV	Min.	Max
Vaccine Prioritisation	0.873057	0.8534356	0	2
Testing Policy	2.030586	0.6971163	0	3
Confirmed Cases	1730554	3235406	0	1.83E+07
Confirmed Deaths	36487.77	49725.72	0	159570
Medically Clinically Vulner.	1.695349	0.6388559	0	2
Vaccination Policy	2.433108	2.251171	0	5
School Closing	1.49352	0.995236	0	3
Work Place Closing	1.870918	0.9473729	0	3
Cancel Public Events	1.521255	0.7519325	0	2
Restrictions on Gatherings	2.904355	1.672863	0	4
Close Public Transport	0.7517025	0.4320819	0	1
Stay at Home Requirements	0.6505962	0.810708	0	2
International Restrictions	2.049248	1.132938	0	3
Contact Tracing	1.104226	0.4589195	0	2
Stringency Index	55.3684	23.05238	0	87.96

Source: Oxford COVID-19 Government Response Tracker (OxCGRT).

In terms of household financial related data (see Table 2), the frequency of our data is monthly, and the data source is the Bank of England, Money, and Credit Statistics from the beginning of the pandemic January 2020 to February 2022. Moreover, the main variables we employ are: total repayments; gross lending; net lending; deposits average interest rate; interest rate credit card lending; net consumer credit lending; net consumer credit; net credit card lending; net consumer credit excluding credit; total sterling net credit card lending; approvals for re-mortgaging; approvals for other secured lending; approvals for house purchase.

Table 2: Household finances related data.

Variables	Mean	Std. dev.	Min	Max
Total Repayments	18246.38	2892.265	13898	27851
Gross Lending	23217.71	6513.173	14526	43119
Net Consumer Credit	-141.3333	894.1521	-2921	951
Net Secured Lending	5078.917	4066.38	-2336	16946
Net Credit Card Lending	-434.75	1338.003	-4850	742
Credit Card Lending	21.05	0.3616974	20.54	21.49
Approvals for Re-mortgaging	37964.83	5837.573	30584	52510
Approvals for other secured lending	12531.38	2395.774	6043	14584
Approvals for house purchase	73464.38	23840.89	9279	105365

Source: Bank of England, Money, and Credit Statistics.

5. Empirical results.

5.1 The Marginal Effects on Household Finances.

As a first step we report the marginal effects of Equation (2) and more specifically its general form Equation (3) where COVID-19 fits into daily returns of stock market that in turn would impact upon household debt repayments.

Table 3 below reports the marginal effects of β post mean and γ post mean on the following household financial related data: Debt Repayments; Gross Lending; Net Lending; Deposits average interest rate; Interest Rate of Credit Card Lending; Net Consumer Credit Lending; Net Consumer Credit; Net Credit Card Lending; Net Consumer Credit Excluding Credit; Approvals for Re-mortgaging; Approvals for Other Secured Lending; Approvals for House Purchase.

In detail, the βs capture the autoregression effect, that is the persistence of returns in Equation (1). We also report the γs that are part of the Γ vector from Equations (2) and (3) and capture the impact of COVID-19 variables on household financial data. The results in Table 3 show that there is strong economic and statistical significance across all marginal effects. In terms of magnitude the autoregression effect of stock market returns on household debt repayments is very low, implying that a shock in equity returns will be transitory and last for a short time.

Table 3. Marginal effects on household finance variables.

	Debt Repayments	Gross lending	Net lending	Deposits average interest rate	Interest rate of credit card lending	Net consumer credit lending
β post mean	0.006164	0.1981	0.2734	0.2569	0.968	0.8711
post sd	0.4796	0.3088	0.04624	0.1073	0.09365	0.2007
post z	4.17	6.476	43.25	18.64	21.36	9.966
γ post mean	-0.5029	-0.4398	-0.5943	-0.1064	-0.9491	-0.6961
post sd	0.3195	0.3592	0.4389	0.1397	0.008848	0.04072
post z	6.259	5.568	4.557	14.32	226.1	49.12
	Net consumer credit	Net credit card lending	Net consumer credit excluding credit	Approvals for re-mortgaging	Approvals for other secured lending	Approvals for house purchase
β post mean	0.0007291	0.8706	0.514	0.4791	0.7029	0.5616
post sd	0.4888	0.4388	0.1453	0.02738	0.09446	0.03438
post z	4.092	4.558	13.77	73.04	21.17	58.18
γ post mean	-0.3752	-0.9815	-0.3845	-0.6089	-0.225	-0.3975
post sd	0.2378	0.1988	0.001744	0.4722	0.09582	0.06501
post z	8.409	10.06	1147	4.235	20.87	30.76

Source: Authors' estimations.

However, note that there is high magnitude in the marginal effects of *βs* on all other household finance related data and in variables related to credit cards. In some detail, the *βs* for interest rate of credit card lending and net consumer credit lending is 0.968 and 0.8711 respectively whilst are also highly statistical significance (the post z stats are 21.36 and 9.966 respectively). Similarly, the *β* for net credit card lending has a magnitude of 0.8706 and is highly statistically significant (post z stat is 4.558). Those findings imply that a one-time shock in equity returns would have a high impact on credit lending into the next period. It is worth noting that for all variables of interest in the current analysis there is high magnitude and statistical significance in *βs*. It is worth noting that the *β* for household debt repayments is positive but low in magnitude at 0.006 (compared to other *βs*) and highly statistically significant with post z statistic equal to 4.17. Therefore, household debt repayments although are affected by dynamics in equity returns, this impact is lasting short period of time.

In terms of γs clearly COVID-19 negatively affect all household finance variables, including household debt repayments and net lending. In detail, the impact of COVID-19 on household debt repayment as measured by γ is -0.5 (and it is also highly statistically significant with a post z equal to 6.25), implying that COVID-19 will reduce household debt repayments. This result is of some importance as in the beginning of the pandemic in April 2020 secondary statistical data of Bank of England showed that an increase in household debt repayments. Our results show that once we factor into the autoregressive impact of financial markets, that is once we include information from the financial industry that closely affects household financial decision making, COVID-19 is negatively related to household debt repayments. Therefore, the initially reported increase in household debt repayments at the beginning of the pandemic has been a one-time of event that could not have lasted. Subsequent household debt repayments data in the second half of 2020, 2021 and 2022 show that household debt repayments fell. It is worth noting that all γs have a negative sign and are statistically significant with the lower magnitude reported for deposits average interest rate at -0.1 while the highest is reported for net credit card lending at -0.98. The latter parameter estimate for γ implies that COVID-19 severely disrupt lending and credit card lending. This result confirms the prediction of Franklin et al. (2021) that argues constraints in household credit would amplify the negative effect of COVID-19 on household finances.

We shall explore the underlying dynamics in the main variables next using Impulse Response Functions (IRFs).

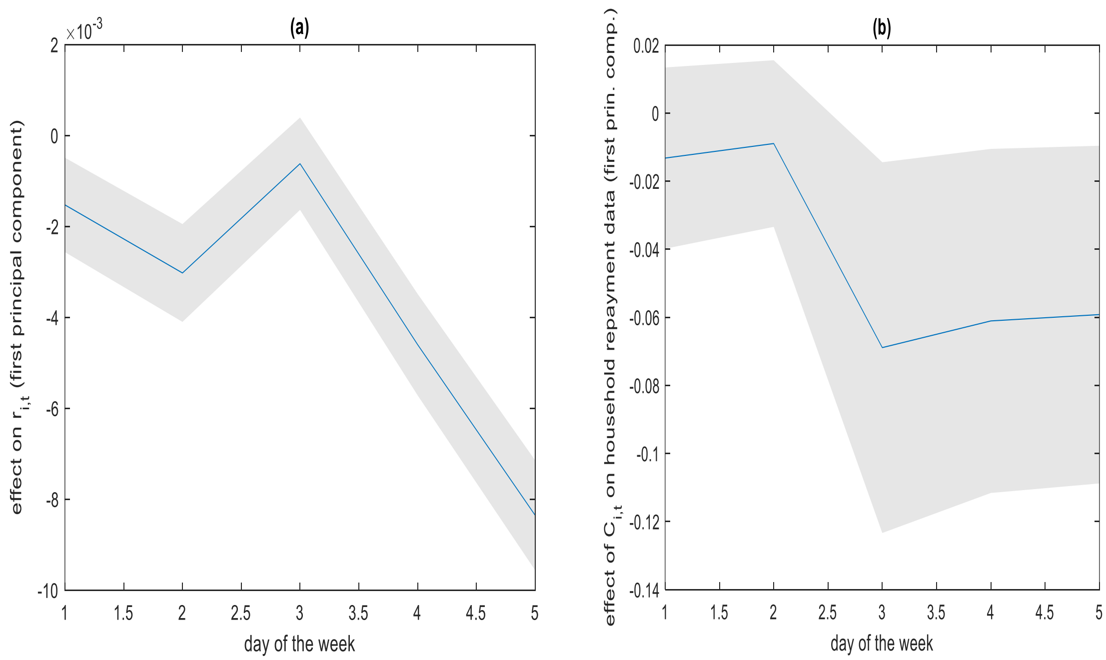
5.2 IRFs of the impact of COVID-19 shocks on equity return and household debt repayments.

In addition to the above results of the marginal effects, we also employ generalized response functions and provide their interactions with government interventions and feedback loops. This is of particular importance given the risk of further waves of the pandemic. Thus, in this section we present the Impulse Response Functions (see for panel VAR Koutsomanoli-

Filippaki & Mamatzakis, 2011; Mamatzakis, 2011 and Mamatzakis & Remoundos 2011) to show primarily the responses of household debt repayments to shocks in the economy as measured by stock returns, that are of high frequency, due to COVID-19.

First, we report how COVID-19-related information impacts on stock returns. As there are $k = 17$ COVID-19 related variables we take their first principal component and show the weekly effects in panel (a) of Figure 5. It is worth noting that if we included all COVID-19 related data will result to overidentification of our modelling that undermine statistical significance, whilst the use of 1st principal component of all COVID-19 data does not suffer from overidentification. Panel (a) in Figure 5 shows that one standard deviation shock in the 1st principal component of COVID-19 will have negative and statistically significant impact on financial markets equity return that is the FTSE-100 index of London Stock Exchange (LSE) in our sample. In detail, a shock in COVID-19 will reduce financial markets return by 0.003 within two days. Thereafter, there is a correction towards the zero line, but by day 5 financial markets equity return will be down by 0.008. Therefore, shocks in COVID-19 show persistence in the short term for financial markets equity return in LSE.

Figure 5. Impulse Response Functions of equity return and household repayment to 1st principal component of COVID-19 related data in United Kingdom.



Source: Authors' estimations.

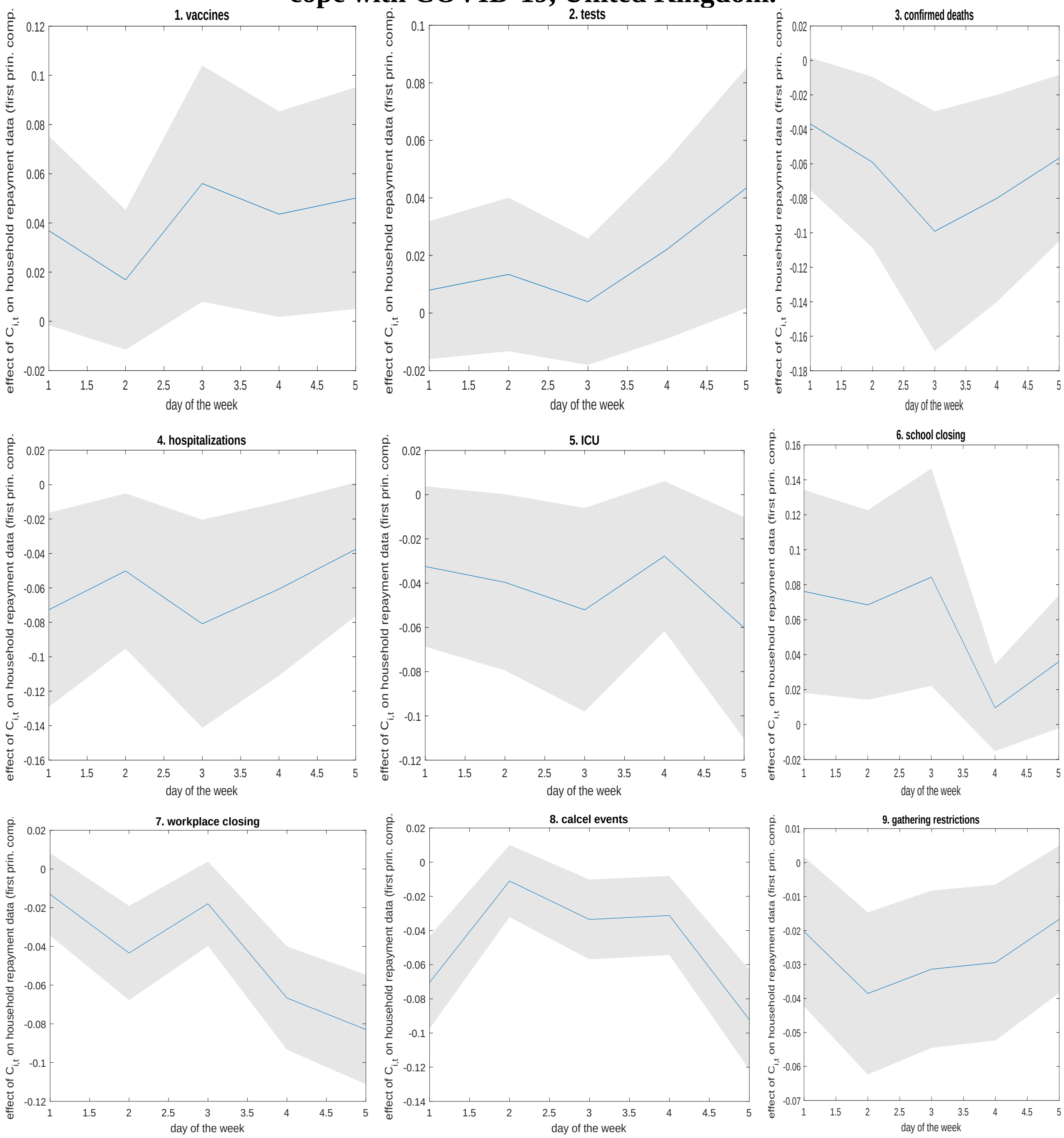
If we do the same IRFs analysis with the $m = 14$ household-level repayment data the results are shown, by day of the week in panel (b) of Figure 5. The response of household debt repayments on one standard deviation shocks in COVID-19-related data (see 1st principal component of COVID-19 as in the case of equity return) is negative across the time horizon, confirming our empirical findings of the previous section. The in panel (b) of Figure 5 shows that a shock in COVID-19 will reduce household debt repayments by 0.007 within three days and it will stabilise thereafter when the standard errors bound become quite wide implying low statistical significance.

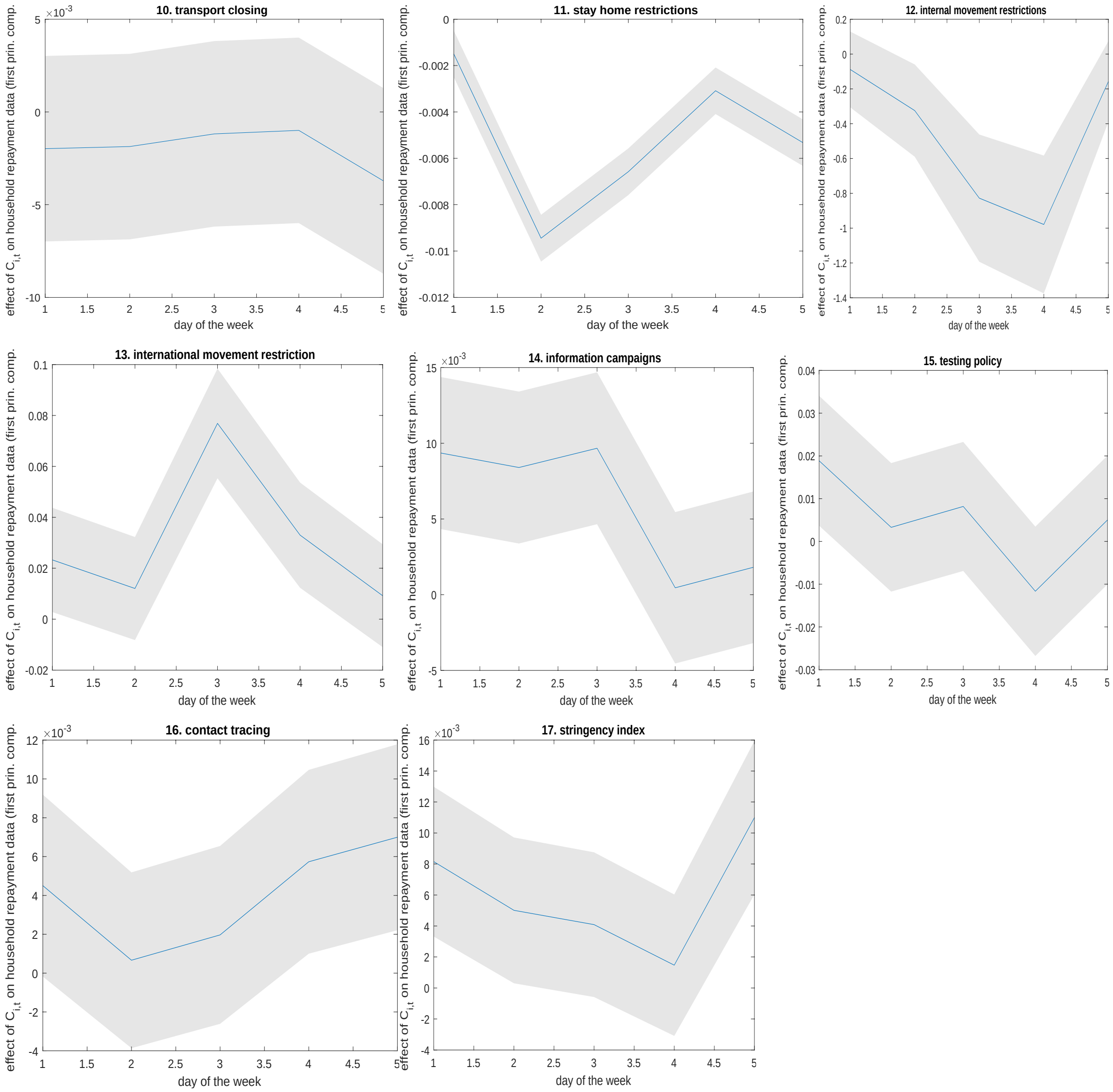
It is worth noting that this is "aggregate" information in the sense that, for simplicity we focused attention on the principal components of COVID-19 (see $C_{i,t}$) and $\mathbf{y}_{jt}$. Our main interest is the specific effect of the $k = 17$ COVID-19-related variables on the household-level debt repayments.

Therefore, we report Figure 6 (for j=1…17) for the UK reports the impulse responses of household debt repayments to various measures to cope with COVID-19. It becomes apparent that there is variability in the responses of household debt repayments to the COVID-19 various data. Mostly, however, the responses of household debt repayments to one standard deviations shock in confirmed deaths, hospitalisations, ICU admissions, workplace closing, cancel events, gathering restrictions, transport closing, stay home restrictions, internal movement restrictions are negative. It is worth noting though that the responses of household debt repayments to one standard deviations shock in vaccines, testing, school closing, international movement restrictions, information campaign, testing policy, contact tracing, and stringency index are positive. These results demonstrate that there is not a one size fit all case. Vaccines, international movement restrictions, testing and the stringent index assert a positive impact on household debt repayments of a magnitude of 0.008. These IRFs testify that one should be cautious when arguing that COVID-19 caused an increase in household debt repayments given that we show that the mostly COVID-19 shock impact negatively in household debt repayments, while the positive responses are low in magnitude. Those results in relation to the first principal component analysis of all

COVID-19 related data show that overall COVID-19 related shocks asserts a negative impact on household debt repayments, and it is a rather a short run type of effect that converges to the equilibrium within a week or so.

Figure 6. Impulse Response Functions of household debt repayments to measures to cope with COVID-19, United Kingdom.





Source: Authors' estimations.

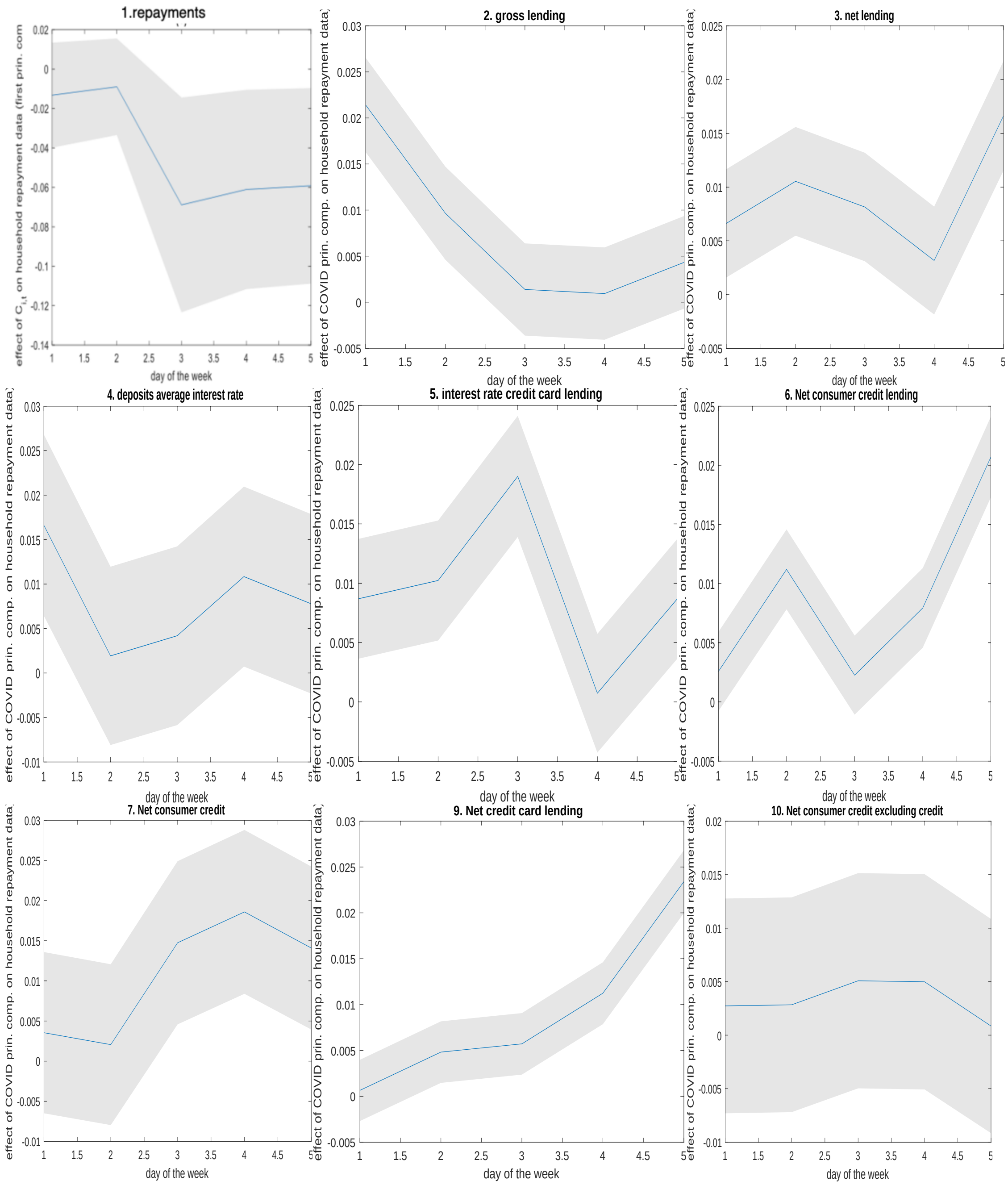
5.3 IRFs of the impact of COVID-19 shocks on household financial variables.

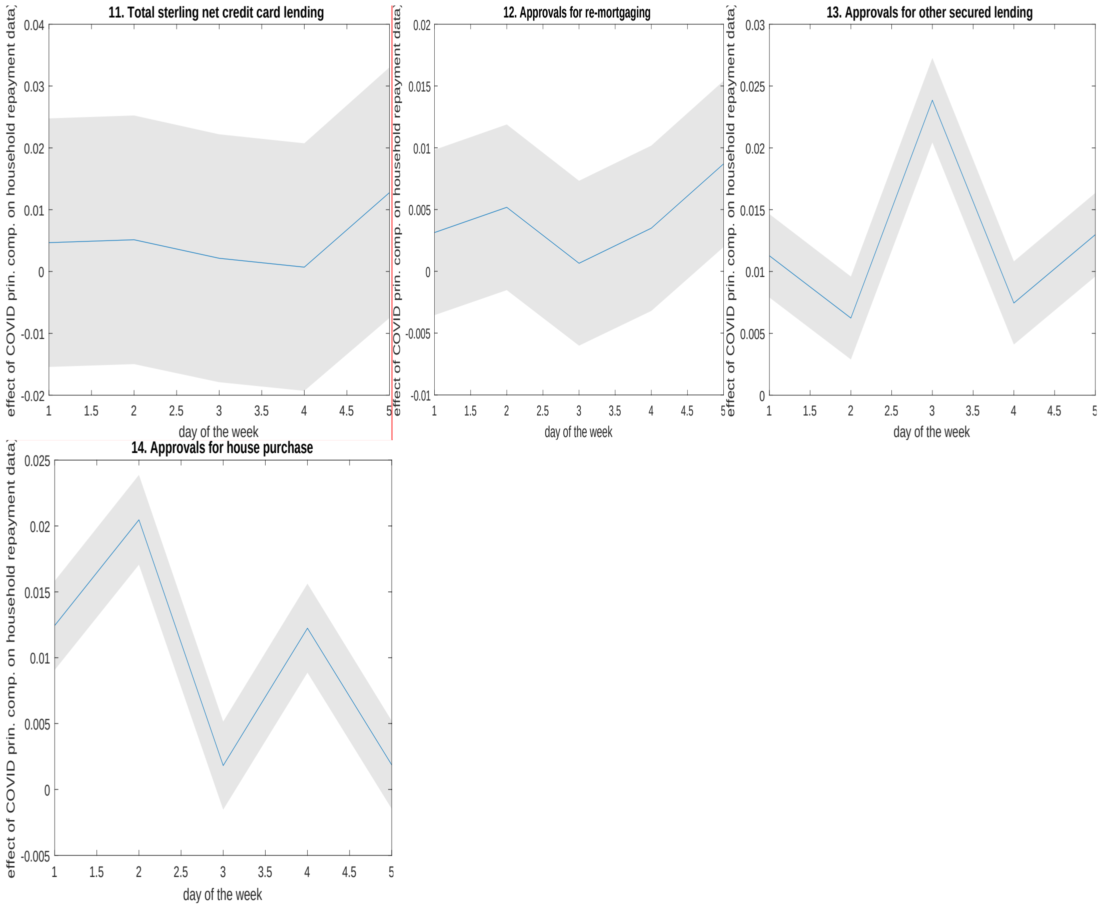
In Figure 7 we report the IRFs that show the responses of various household financial variables (Debt Repayments; Gross Lending; Net lending; Deposits average interest rate; Interest Rate of Credit Card Lending; Net Consumer Credit Lending; Net Consumer Credit; Net Credit Card Lending; Net Consumer Credit Excluding Credit; Approvals for Re-mortgaging; Approvals for Other Secured Lending; Approvals for House Purchase) to shocks of the first principal component of COVID-19-related variables (liked confirmed cases, confirmed deaths etc, see Table 1 for details of the COVID-19 variables). The IRFs show again the that the response of household debt repayments to shocks of the first principal component of COVID-19-related variables is negative in the first few days of the shock and then it is converging thereafter. It is also worth noting that response of gross lending, deposits average interest rate, approvals of other secured lending is negative to shocks in COVID-19 1st principal. Once more we observe the complexities of the underlying relationships as there is no one size fit all case. For example, the responses of net lending, interest rate credit card lending, and net consumer credit lending to shocks in COVID-19 are positive in the first two to three days and turn negative thereafter. Clearly, the shocks from COVID-19 on household financial data is of transitory nature and there is little persistence. However, it is worth noting that the response of net credit card lending on a shock in the 1st principal COVID-19 is positive across all days, implying some persistence. In Appendix we report, for comparison, IRFs for US and Canada. Results show some variability for those countries though overall agree with the UK findings.

The above results add to previous evidence that show COVID-19 interventions would incentivise household debt payment (see Georgarakos and Kenny 2022) as we report that such effects are transitory over a short period of time that lasts less than a quarter. Therefore, as the pandemic spread over two years household debt repayments fall back also considering the gradual facing out of government interventions due to higher fiscal burdens.

Summarising our neural network VAR model reveals that there is variability in the underlying dynamics between household finances and COVID-19. Although most shocks in COVID-19 related data would assert negative effects on household finances. Overall, the impact of 1st principal COVID-19 shock on household finance is negative, while there is some variation over time and net credit card lending could be on the rise because of COVID-19 shocks, though this effect last for five days. According to household financial statistical analysis of impulse response functions, households would cut their debt repayments, and lending to households would also decline. Our findings suggest that UK households not only experience health-related suffering but also financial hardship, and that the pandemic has negatively impacted their finances.

Figure 7. The Impulse Response Functions of the first principal component of COVID-19-related variable to the household financial variables.





Source: Authors' estimations.

6. Conclusions

If, indeed, the increase in household debt repayment of the first six months of the COVID-19 lockdown were to last, it could have caused a structural change in the financial industry. Our results show that household debt repayments' response to the first principal component COVID-19 shocks is negative, albeit of low magnitude. However, when we employ specific COVID-19 related data like vaccines and tests the responses are positive, insinuating the complexities of the underlying relationships. Overall, though, main COVID-19 data such as confirmed deaths and hospitalizations negatively affect household debt repayments. The neural network VAR MIDAS reveal that there is low persistence in household debt repayments and other household financial data. Generalized impulse response functions confirm this main result.

Prior research Franklin et al. (2021) argue that many UK households have managed to weather the crisis of COVID-19, though authors also argue that households with unsecured loans could face financial difficulties. In this paper we provide evidence that the observed household debt repayments in the beginning of the pandemic were bounced back thereafter as COVID-19 negatively affected household finances, including household debt repayments. We also find that not all government COVID-19 interventions improve household debt repayments as reported in Georgarakos and Kenny (2022). Our impulse response functions show that vaccines and testing would positively affect household debt repayments, but draconian measures like workplace closing and transport restrictions would undermine household debt repayments. Our findings are in line with the Franklin Et al. (2021) that argue that household debt could amplify exogenous shocks, like economic shocks or the pandemic. In detail our findings shows that COVID-19 shocks adversely affect mainly household credit and thereby household finances.

Tarne et al. (2022) argue that enhancing access to credit to the households with lower level of assets, like first time property buyers, leads to the most substantial reductions in household debt, wealth inequality and consumption volatility. Our findings confirm that providing credit and lending to households is key to overcome the negative shock of COVID-19 on household finances.

Our results are supported by the recent data showing that households debt repayments have fallen behind in 2021 and in 2022. The prolonged uncertainty over the pandemic and the associated credit and lending restrictions, whilst in recent months hikes in interest rates increase the cost of household borrowing, have adversely affected household finances and in particular household debt repayments.

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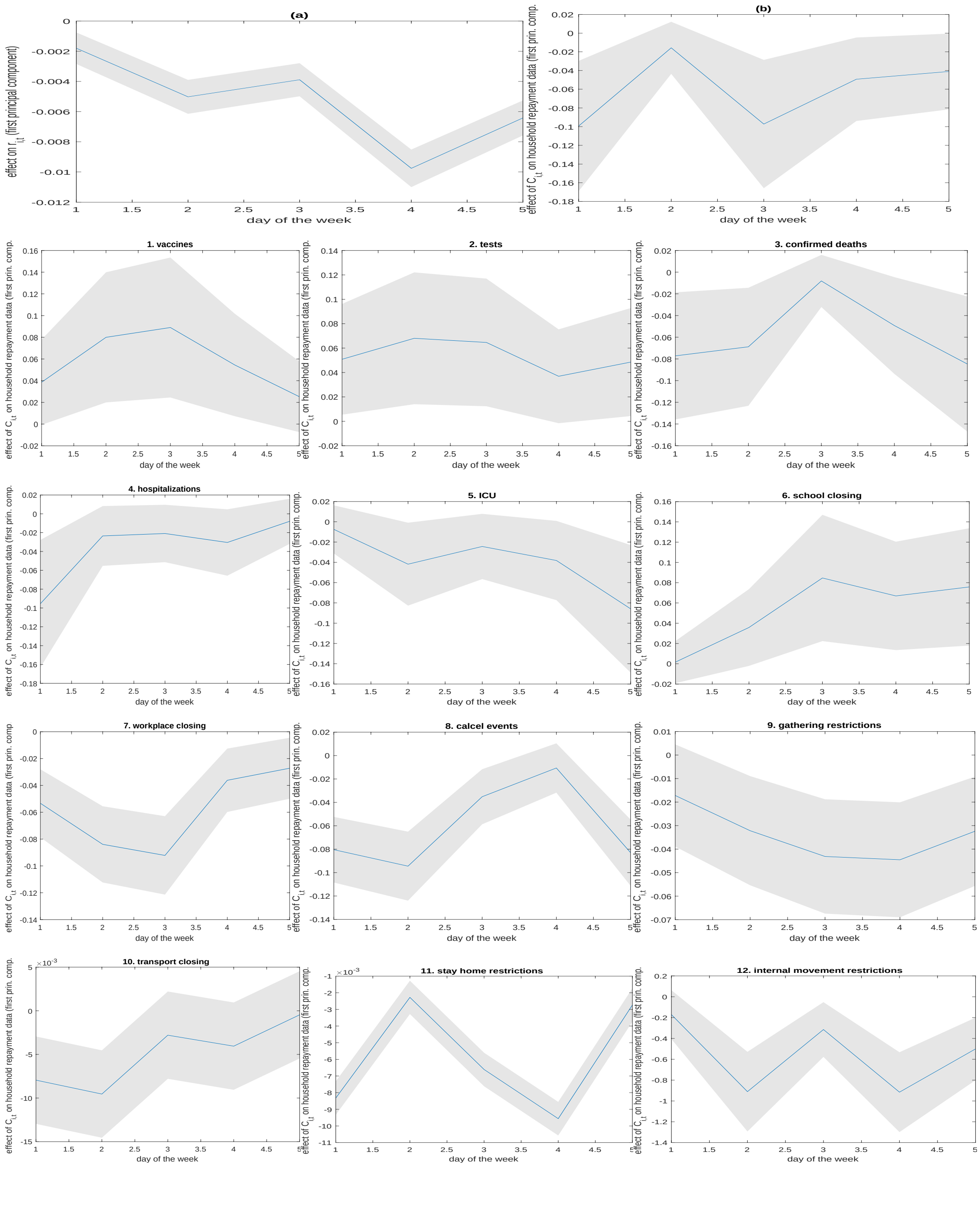
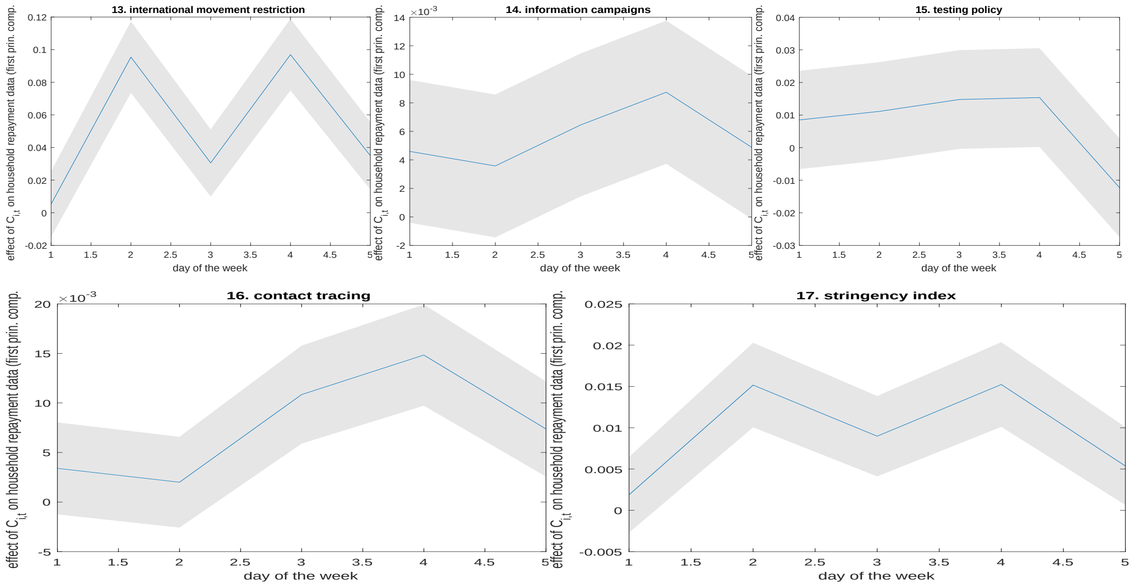
Appendix

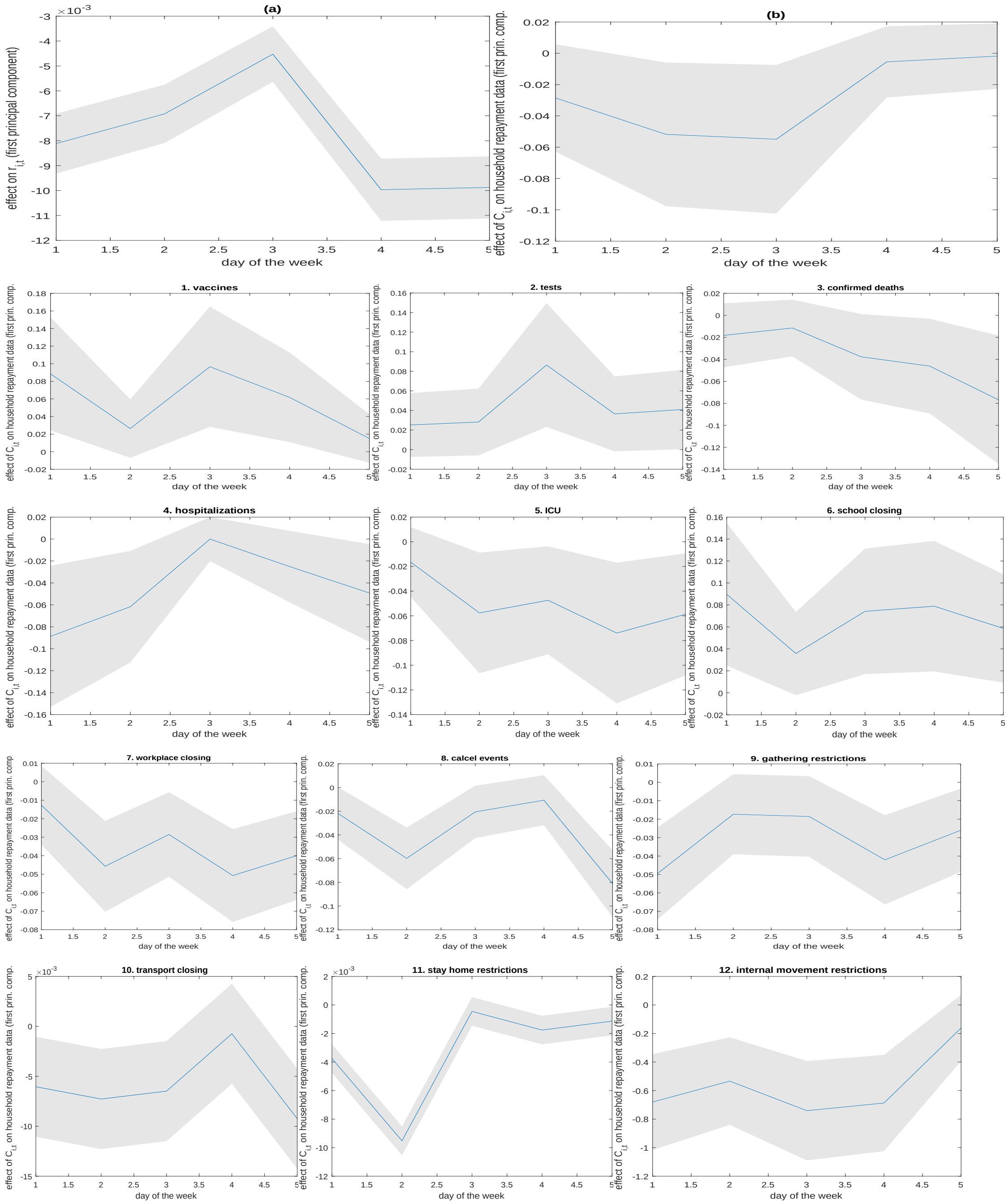
Figure A1 we report the effect of each COVID-19 related variable on the first principal component of household repayments in USA and the impact of COVID-19 of household financial data.

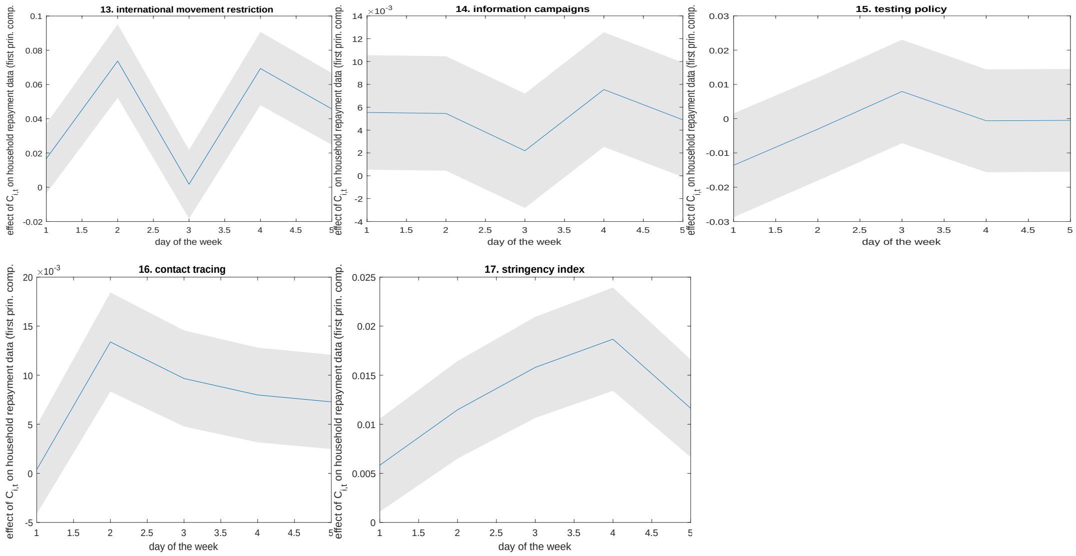




Source: Authors' estimations.

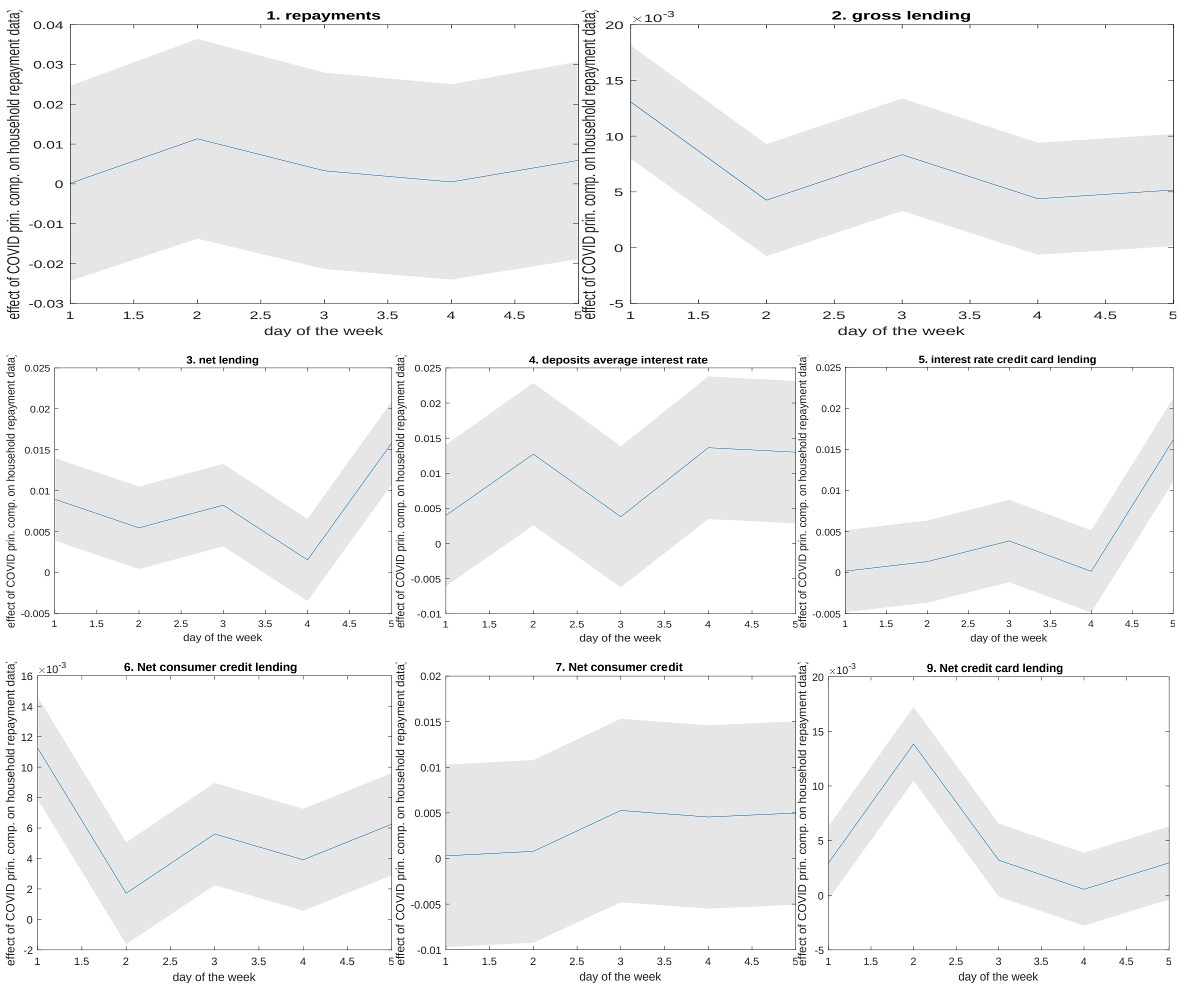
Figure A2 we report the effect of each COVID-19-related variable on the first principal component of household repayments in Canada.

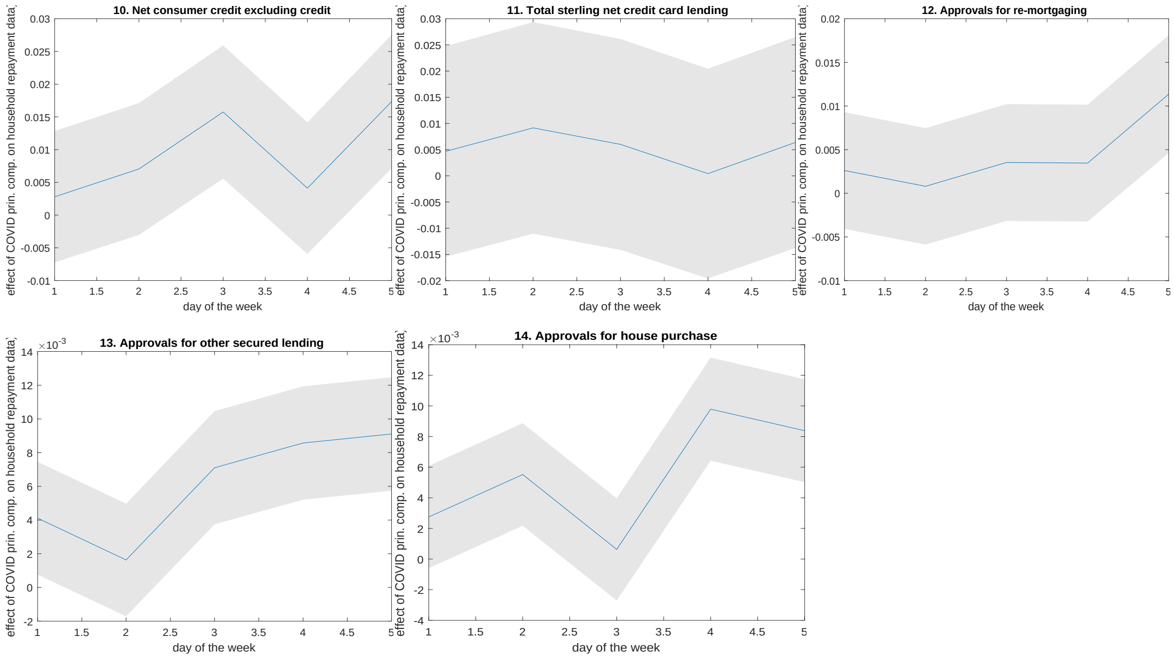




Source: Authors' estimations.

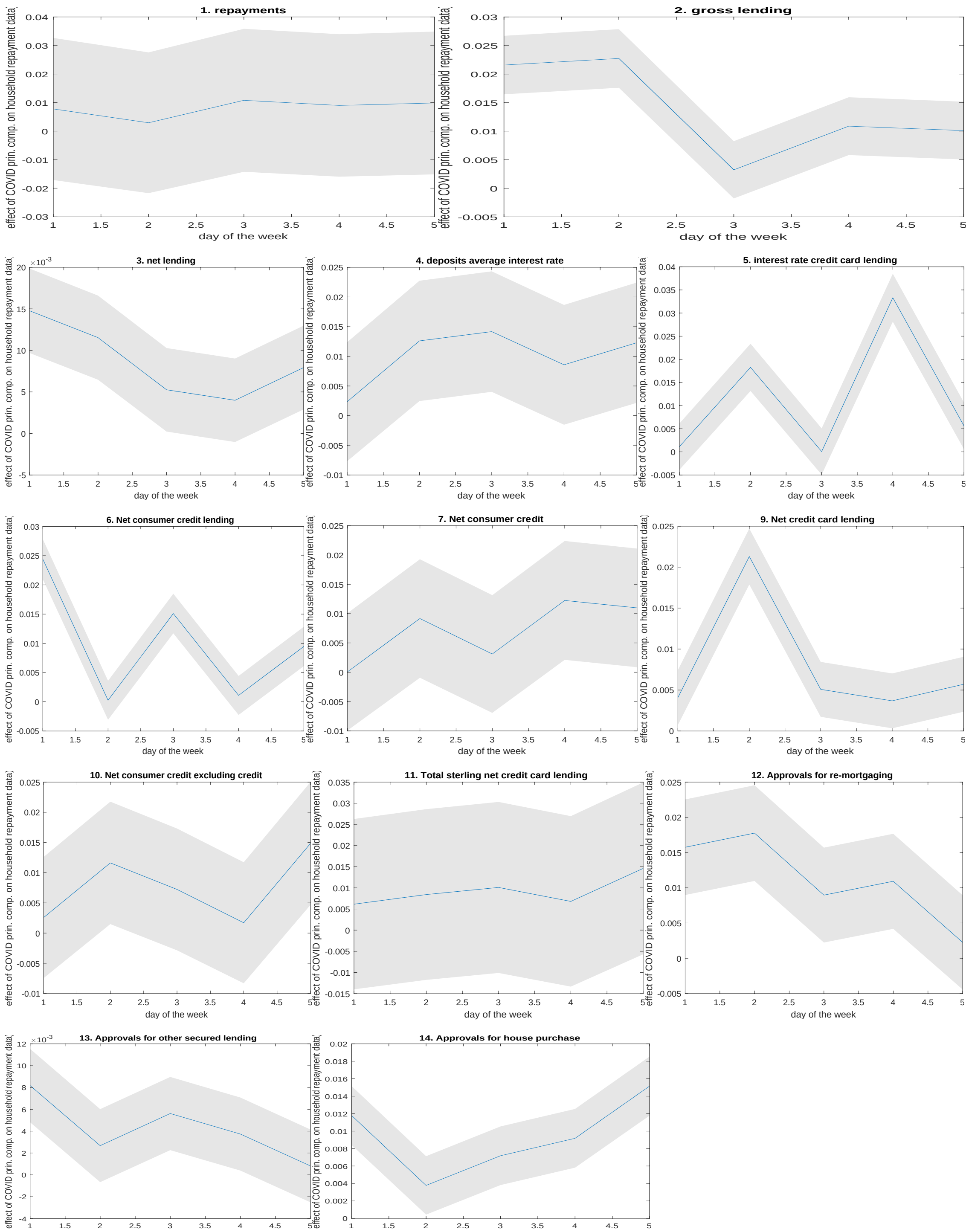
In Figure A3 we report the effect of the first principal component of COVID-19-related variable on the different aspects of household repayments for USA.





Source: Authors' estimations.

In Figure A4 we report the effect of the first principal component of COVID-19-related variable on the different aspects of household repayments for Canada.



Source: Authors' estimations.