Online Appendix for Monetary Policy and Liquidity Constraints by Mattias Almgren, José-Elías Gallegos, John Kramer and Ricardo Lima

As a robustness check to our main empirical framework, we construct an instrumented GVAR. We build a more structural –and restricted– setting than the LPIV, more similar to the widespread VAR estimation in the literature. We follow the GVAR setting in Burriel and Galesi (2018), except that we remove contemporaneous variables on the right hand side for endogeneity issues. All N economies are represented by the following system:

(B1)
$$\Lambda Q_t = \kappa_0 + \sum_{j=1}^r K_j Q_{t-j} + \nu_t$$

where $Q_t = (y_{1t}, \pi_{1t}, ..., y_{Nt}, \pi_{Nt}, i_t)'$ is a $(2N+1) \times 1$ vector containing output and inflation for each country, and the global interest rate. Pre-multiplying both sides by Λ^{-1} yields

(B2)
$$Q_t = h_0 + \sum_{j=1}^r H_j Q_{t-j} + v_t$$

where $h_0 = \Lambda^{-1}\kappa_0$, $H_j = \Lambda^{-1}K_j$ and $v_t = \Lambda^{-1}v_t$. We seek to estimate (B2). Unfortunately, this is unfeasible due to the curse of dimensionality: there are too many parameters to estimate for the restricted number of observations that we have. In order to overcome this situation, we borrow two key assumptions from the GVAR literature: we assume that (i) foreign variables affecting country i will be a composite of an aggregate coefficient and the trade weight to each foreign economy, and (ii) that the ECB reacts to euro area aggregates and not to individual countries. In this way, our setting is akin to a standard GVAR but without assuming the Small Open Economy framework that is necessary to rule out potential endogeneity biasness.

We now explore each equation inside the (B2) system. We start with the first block, that includes the Dynamic IS curve and the New Keynesian Phillips curve. Each domestic economy is represented by the following reduced-form VAR:

(B3)
$$Y_{it} = c_i + \sum_{j=1}^{p_i} A_{ij} Y_{i,t-j} + \sum_{j=1}^{q_i} B_{ij} Y_{i,t-j}^* + \sum_{j=1}^{q_i} C_{ij} X_{t-j} + u_{it}$$

where c_i is a country specific intercept vector, Y_{it} is a 2×1 vector of domestic variables (i.e., output and inflation), Y_{it}^* is a 2×1 vector of aggregate foreign variables, X_t is a the ECB policy rate and u_{it} is a vector of idiosyncratic country-specific

reduced form shocks. The foreign variables are computed as trade weighted aggregates $Y_{it}^* = \sum_{j \neq i} w_{ij} Y_{jt}$ with $\sum_{j \neq i} w_{ij} = 1$, where we assume that weights w_{ij} are fixed over time. Stacking all countries in our model, using that $Y_{it}^* = W_i Y_t$ with W_i being country-specific weight matrices, we can write equation (B3) as

(B4)
$$Y_t = c + \sum_{j=1}^{p} G_j Y_{t-j} + \sum_{j=1}^{q} C_j X_{t-j} + u_t$$

where
$$G_j = (A_j + B_j W)$$
, $Y_t = (Y'_{1t}, \dots, Y'_{Nt})'$, $u_t = (u'_{1t}, \dots, u'_{Nt})'$, $c = (c'_1, \dots, c'_N)'$, $C_j = (C'_{1j}, \dots, C'_{Nj})'$, $p = \max(p_i, q_i)$ and $q = \max(q_i)$.

Next, the second building block consists of variables which affect all countries, i.e. the interest rate controlled by the ECB,

(B5)
$$X_{t} = c_{x} + \sum_{j=1}^{p_{x}} D_{j} X_{t-j} + \sum_{j=1}^{q_{x}} F_{j} \widetilde{Y}_{t-j} + u_{xt}$$

where u_{xt} is a vector of idiosyncratic reduced-form shocks and \widetilde{Y}_t is a weighted average of all countries' domestic variables, with weights based on GDP shares $\widetilde{Y}_t = \widetilde{W}Y_t = \sum_j \widetilde{w}_j Y_{jt}$ with $\sum_j \widetilde{w}_j = 1$.

Notice that equation (B5) is no more than a standard Taylor rule that the ECB is assumed to follow: the current interest rate depends on lags of output and inflation, plus lags on the interest rate itself. Stacking the two blocks given by (B4) and (B5), we obtain the following system of equations, which is exactly the same as in (B2),

(B6)
$$Q_t = h_0 + \sum_{j=1}^r H_j Q_{t-j} + v_t$$

where $r = \max(p, s)$, and the vector $Q_t = (Y_t', X_t')'$ includes all country-specific and common variables, $h_0 = \begin{bmatrix} c \\ c_x \end{bmatrix}$, $H_j = \begin{bmatrix} G_j & C_j \\ F_j \widetilde{W} & D_j \end{bmatrix}$ and $v_t = \begin{bmatrix} u_t \\ u_{xt} \end{bmatrix}$ In our baseline estimation, we set $p_i = q_i = 3 \ \forall i \in \mathbb{N}$, and $p_x = q_x = 3$.

A novelty in this paper is that we identify monetary responses in a GVAR setting using exogenous instruments. In particular, we identify the structural monetary policy shock from the reduced-form errors. The structural error vector can be written as $v_t = \begin{pmatrix} u_t \\ u_{xt} \end{pmatrix} = \Lambda^{-1} \begin{pmatrix} \varepsilon_t \\ \varepsilon_{xt} \end{pmatrix}$. Λ^{-1} being unknown, we would not be able to obtain the true impulse responses. We use external instruments to identify (part of) Λ^{-1} . Since we are only interested in a monetary policy shock, we need to identify the relevant column of the variance-covariance matrix that describes the effect of ε_{xt} on the other structural errors in v_t .

The first part of the identification strategy is similar to the LPIV: we estimate the model in equations (B3) and (B5) using OLS. As before, one can verify that the reduced form errors v_t are linear combinations of the structural errors $\varepsilon_{it} \ \forall i \in N \ \text{and} \ \varepsilon_{xt}, \ \text{where} \ \Lambda^{-1} \ \text{is a} \ 2N+1 \ \text{square matrix with elements on}$ its 2×2 block diagonal and zeroes elsewhere. Without further restrictions, we cannot identify the full matrix Λ^{-1} describing the relationship between reduced form and structural errors. We can, however, identify the column of the matrix describing the influence of the structural component of the interest rate ε_{xt} on the other variables. The relevant column of Λ^{-1} can be identified by introducing the contemporaneous interest rate on the RHS of the system of equations (B3), making use of 2SLS. Following Stock and Watson (2018), we identify the relative response a variable j to a structural shock in x in two steps. First, we instrument X_t using a valid instrument satisfying $\mathbb{E}[Z_t \varepsilon_{xt}] = \alpha$ and $\mathbb{E}[Z_t \varepsilon_{jt}] = 0$ where $j \neq x$, and regress the contemporaneous interest rate on the instrument Z_t , lags of the instrument and the rest of the variables that will enter the second stage of the 2SLS estimation:

$$X_{t} = c_{i} + \sum_{j=1}^{p_{i}} A_{ij} Y_{i,t-j} + \sum_{j=1}^{q_{i}} B_{ij} Y_{i,t-j}^{*} + \sum_{j=1}^{s_{i}} C_{ij} X_{t-j} + \theta_{ix}^{SW} Z_{t} + u_{it}$$

From this first stage we obtain the fitted policy rate \widehat{X}_{it} and we can then estimate the system (B7). Second, we estimate the following system of equations for every country i,

(B7)
$$Y_{it} = c_i + \sum_{j=1}^{p_i} A_{ij} Y_{i,t-j} + \sum_{j=1}^{q_i} B_{ij} Y_{i,t-j}^* + \sum_{j=1}^{s_i} C_{ij} X_{t-j} + \Theta_{ix}^{SW} \widehat{X}_{it} + u_{it}$$

The contemporaneous effect of a monetary policy shock on other variables is captured through Θ_{ix}^{SW} , which is used together with the endogenous variables' coefficient matrix to obtain the impulse responses.

B2. Panel LPIV

In Figure 9b, we compare the average impulse responses of output in two sets of countries: those with high and low levels of liquidity constrained individuals, according to our HtM variable. This approach does not allow for country-specific heterogeneity beyond the two HtM categories. Hence, in this section, we estimate a Panel LPIV which allows us to control for country fixed effects in addition to the high/low-HtM dummy.

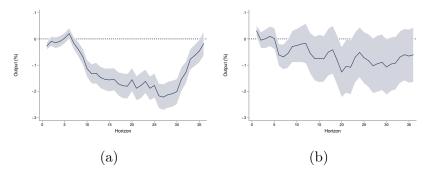
We run the following regression, following Jordà (2005), as before:

$$y_{n,t+h} - y_{n,t-1} = \alpha^h + \beta^h \hat{i}_t + \delta^h \widehat{i}_t \times htm_n + \gamma_n^h$$
(B8)
$$+ \xi_n^h htm_n + \sum_{j=1}^p \Gamma_{n,j}^h htm_n X_{t-j} + u_{n,t+h}, \quad h = 0, \dots, H$$

where y_n is log of output in country n, \hat{i} and $\hat{i_t} \times htm_n$ are the fitted values from the first-stage regression, htm_n takes value of 0 if the HtM share in a country is below the median value across all countries and 1 otherwise, and γ_n^h represents the country fixed effects. The control variables X_{t-j} are the same for all countries, namely lags of euro area real GDP, euro area HICP, lags of the policy variable and lags of the instrument Z. We interact these control variables with the htm dummy. We construct the instrument for $i_t \times htm_n$ by multiplying our instrument for the policy rate, Z_t with the high-HtM dummy: $Z_t \times htm_n$.

The coefficient of interest in this estimation is δ_n^h , which measures the additional impact of an interest rate change on real GDP in countries with higher-than-median shares of HtM individuals, beyond the impact already captured in β_n^h .

Figure B1 plots both coefficients across horizons h. The left panel indicates that GDP falls for all countries, in response to a one standard deviation shock. As already suggested in Figure 9b in the main body of the paper, however, GDP falls by significantly more in countries with a higher share of HtM households. The crucial difference between the two exercises is that here, we are able to control for country-specific fixed-effects beyond the high/low-HtM classification. We view the fact that the conclusions are unchanged as encouraging.



Note: The Left Panel plots the coefficient β^h from Equation (B8) for each horizon h in response to a one standard deviation shock to our instrument. The Right Panel plots the coefficient δ^h from Equation (B8). The blue shaded area represents 1 standard deviation confidence bands.

Figure B1. Panel LPIV

B3. European Overnight Indexed Swap Data

We obtain a minute-frequency series for Eonia Overnight Indexed Swaps from Datastream. We compute the fixed rate of the swap as the mid point between the bid and ask price at the close of each minute. We then drop all dates from the sample that are not ECB announcement dates.

The resulting series contains implausible outliers, e.g. the rate decreasing to zero for one minute, or short fluctuations of more than 5 standard deviations. Consequently, we drop the highest and lowest percentile of observations on each announcement day. Lastly, we manually drop remaining implausible observations if they fall within either of the two announcement windows.

For our final series, we exclude the observation on November 8th, 2008. On this day, the ECB cut interest rates by 75 BP, by far the largest cut during our sample period. However, the market reaction in the overnight indexed swap rates indicates that markets perceived it as contractionary. Likely, this is due to the Bank of England having lowered its policy rate by 50 BP hours prior. Including the observation does not change our results or the conclusions, except for the first stage F-statistic, which falls to 4.4.

B4. Obtaining HtM Shares Using Data from the HFCS

The HFCS imputes data for missing values related to assets, liabilities and income variables. Our calculations are partly based on these imputed data. A missing value is imputed five times (multiple imputation), where each time a different random term is added to the predicted value. If this would not be done, imputation uncertainty would not be taken into account. This has the consequence that statistics can vary between implicates.

To find point estimates for the statistics based on HFCS data, we average over all the implicates. We consistently use the cross-sectional (full sample) weights, which are mainly intended to compensate for some households being more likely to be selected into the sample than other. In other words, if a type of household has been over-sampled, then they are given less weight in the estimation.

We use techniques that are standard when computing variance estimates for multiple imputed survey data. In short, there are two sources of uncertainty that we need to account for. The first (B) is the uncertainty that is associated with the imputation. This is given by the variance of the point estimates (using the full sample weights). The second (W) is the uncertainty associated with sampling and the weights that should be given each observation. The HFCS contains 1,000 replicate weights and the uncertainty for a statistic associated with sampling and weights is given by the variance of the estimators from using different replicate weights, averaged across the implicates. The total variance, T, is given by $T = W + \frac{6}{5}B$. We refer the reader to the HFCS user manual for more details about finding the variance estimates.

Before we label households, we drop observations where the age of the reference person in the household is below 20 or above 80. As in Kaplan, Violante and Weidner (2014) we drop observations when the only income that the household receives is from self-employment. The results do not change markedly if we choose to keep these observations.

We need to categorize variables as liquid wealth, illiquid wealth, liquid debt and illiquid debt. We follow Kaplan, Violante and Weidner (2014) to a large extent. In Table B1 we present what variables go into respective category and the *Name* refers to its unique name in the HFCS data. The difference between how we categorize the variables and how Kaplan, Violante and Weidner (2014) do it is that we categorize saving accounts as liquid assets while they categorize it as illiquid for the European countries. We choose to categorize it as liquid as it is our view that households can, in general, make adjustments to the balance on saving accounts without incurring substantial costs. In the Panel Study of Income Dynamics (PSID), saving accounts are combined with other assets such as checking accounts. Moreover, in the calibration of the model in Carroll et al. (2017), saving accounts are categorized as liquid.

In the calculation of HtM shares, Kaplan, Violante and Weidner (2014) assume that households on average are paid bi-weekly. In our calculations we will assume that households on average are paid once every month, which we believe is a more accurate assumption about the payment frequency in European countries. We define liquid wealth = liquid assets - liquid debt and illiquid wealth = illiquid assets - illiquid debt.

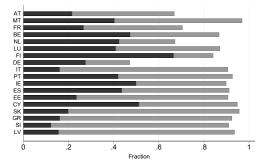
Table B1— Classification of Income and assets in the HFCS

Name		
	Description	comment
Income		
di1100	employee income	
di1610	unemployment benefits	
di1620	other social transfers	
hg0210	income from regular private transfers	
di1510	gross income from public pensions	
Liquid assets		
hd <u>i</u> 110	value of sight accounts	scaled by 1.0556 to adjust for each missing in the HFCS. a
da2102	mutual funds, total	
da2105	shares, publicly traded	
da2103	bonds	
hd1210	value of saving accounts	Illiquid in Kaplan, Violante and Weidner (2014)
Illiquid assets		
hb0900	current price of household main residence	
hb280x	other property \$x: current value	$x = \{1, 2, 3\}$
hb2900	additional properties current value	
sum of pf0710 across HH members	current value of all occupational pension	
	plans that have an account	
da2109	voluntary pension/whole life insurance	
Liquid debt		
hc0220	amount of outstanding credit line/overdraft balance	
hc0320	amount of outstanding credit cards balance	
Illiquid debt		
hb170x	HMR mortgage \$x: amount still owed	$x = \{1, 2, 3\}$
hb370x	other property mortgage \$x: amount still owed	$x = \{1, 2, 3\}$
hb4100	money still owed on additional other property loans	
hb2100	money still owned on additional HMR loans	
m hc080x	non-collateralised loan \$x: outstanding balance of loan hollsty counted if hollstyse < 2	$x = \{1, 2, 3\}$

 $^a\mathrm{This}$ adjustment follows Kaplan, Violante and Weidner (2014).

B5. Tenure status, mortgages and HtM status

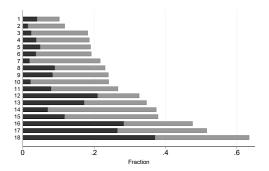
Ownership Rates and Mortgages Among W-Htm Households. — Figure B2 shows that the majority of households who have been classified as W-Htm households own the property in which they live (represented by the total length of each bar). However, in most countries the majority of W-Htm households do not have a mortgage (black). The countries are ordered according to their shares of W-Htm households, with the country with the lowest share of W-Htm households on top (Austria).



Note: This figure shows three things: (i) the fraction of W-HtM households who own the residence in which they live (total length of each bar), (ii) the fraction of W-HtM households who have a mortgage (black) and the fraction of W-HtM who own their residence but do not have a mortgage (gray). The countries are ordered according to their shares of W-HtM households, with the country with the lowest share of W-HtM households on top (AT). The fractions are computed using data from the Eurosystem Household Finance and Consumption Survey (HFCS).

Figure B2. Ownership and mortgages among the Wealthy HtM

HTM STATUS AMONG HOMEOWNERS. — Cloyne, Ferreira and Surico (2020) find that the consumption responses of homeowners are significantly smaller than the consumption responses of mortgagors and renters. They use data from the U.K. and U.S. and classify very few homeowners as Hand-To-Mouth (see Figure 10 in their paper). In our data, however, homeowners make up a substantial fraction of HtM households in many countries (see Figure B3). In some countries, it is even the case that a majority of HtM households are homeowners. Hence, we do not think that our results contradict the mentioned study, since homeowners appear to have different characteristics in the countries in our sample, compared to homeowners in the U.K. or the U.S.



Note: This figure divides HtM shares (total length of each bar) up in to households who are homeowners (black) and not homeowners (renters or mortgagors, gray). The countries are ordered according to their share of HtM households, with the country with the lowest share of HtM households on top (MT). The fractions are computed using data from the Eurosystem Household Finance and Consumption Survey (HFCS).

Figure B3. HtM status among homeowners

B6. Local Projections Data

Inflation: We obtain the monthly Harmonized Index of Consumer Prices for all items for all countries in our sample and the euro area from Eurostat (prc_hicp_midx). Industrial Production: We obtain monthly values for Industrial Production (excluding construction) from Eurostat. The series is seasonally and calendar adjusted (sts_inpr_m). Because Ireland changed its formula for the calculation of some national aggregates, we make some assumptions to keep the series as coherent as possible. The change affects the value of Industrial Production in the first two months of 2015, resulting in growth rates in excess of 10%. We substitute these two growth rates with the average growth over 2014, which results in a level shift for all IP values after March 2015.

Unemployment rate: We obtain monthly values of the unemployment rates for all countries in our sample from Eurostat (une_rt_m) . The rates are measured for the active population aged 25 to 74 and are seasonally and calendar adjusted. For Estonia, the value of January 2000 is missing. We obtain it from the OECD (LRHUADTT). The rest of the series coincides with the values from Eurostat.

Real GDP: We obtain the quarterly values for Real GDP for all countries in our sample from Eurostat $(namq_10_gdp)$. The series measures chain-linked volumes of Gross Domestic Product and is seasonally and calendar adjusted. Again, we adjust the series of Ireland due to implausibly high GDP growth in the first quarter of 2015. We substitute the reported growth rate in 2015Q1 with the average growth rate during 2014, which results in a level shift of all subsequent observations.

Eonia: We obtain values for the European OverNight Index Average from Eurostat (irt_st_m) .

Retail trade: We obtain monthly data on Retail trade, except of motor vehicles

and motorcycles from Eurostat for all countries in our sample. The series refers to deflated turnover and is seasonally and calendar adjusted (sts_trtu_m).

Consumption: We obtain data on the final consumption expenditure of households from Eurostat $(namq_10_fcs)$. The series is seasonally and calendar adjusted.

GDP per Capita: We obtain data on Real GDP per capita in 2008 from Eurostat ($SDG_{-}08_{-}10$).