Social transfer multipliers in developed and emerging countries: The role of hand-to-mouth consumers*

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Abstract

This paper estimates the macroeconomic effects of social transfer payments to individuals for a sample of 23 developed and Latin American countries. We find that the on impact social transfer multiplier is 0.3 in developed countries, but 0.9 in Latin American economies. We study the role of hand-to-mouth consumers, who have no access to financial markets and a high marginal propensity to consume, as a first order factor to explain the heterogeneity in the size of social transfer multipliers. Using survey-based data from the Global Findex dataset, we first find that the average share of the population living hand-to-mouth is 23% in developed economies versus 60% in Latin American countries. We interpret this evidence with a two-agent New Keynesian model. We find that the difference in the share of hand-to-mouth consumers is able to explain 80% of the difference in the estimated social transfer multipliers. We also document that the share of hand-to-mouth individuals in emerging countries is in general 47% which suggests that a larger social transfer multiplier may be expected for this type of economies.

Keywords: fiscal transfer, social transfer, fiscal policy, fiscal stimulus, government spending, multiplier, hand-to-mouth, emerging markets.

JEL Classification: E62, E63.

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1 Introduction

The macroeconomic effects of fiscal policy regained great interest since the Global Financial Crisis. This relevance has been recently redoubled as governments around the world evaluate the use of alternative fiscal instruments at their disposal to cope with the COVID-19 pandemic. A category of spending that has been receiving particularly growing attention is social transfers. Social transfers comprise both ongoing social protection programs and emergency policy responses. Ongoing social protection programs refer to the disbursement of government funds to individuals who meet certain eligibility criteria. The main categories include unemployment benefits, family programs, and pensions. On average, social transfers currently account for more than 50 percent of primary government spending in developed countries and about 40 percent in emerging markets (Galeano et al., 2021). In terms of emergency social transfers, for example, some policy responses to COVID-19 have proven to be among the largest in history.[1] In spite of this growing relevance, little is known about the effect that a $1 change in social transfers has on the aggregate level of GDP –the so-called social transfer multiplier (STM, hereafter).[2]

This study contributes to the growing literature on the size and acting mechanism of STMs providing new empirical evidence on the size of STMs on a sample of six Latin American countries and 17 developed economies. Including six middle-income Latin American economies offer an ideal laboratory to further understand the implications played by the allocation of social transfers and, especially, limited access to financial markets in the context of STMs. While there are a handful of empirical studies estimating STMs for developed countries, there is little evidence for emerging markets. Existing empirical studies vary among several critical dimensions including the identification strategy, scope of the social transfer metric, econometric methodology, and country(ies) analyzed. Therefore, it is no surprise that there is little agreement in terms of the size of the STM with empirical estimates ranging widely. In a meta-regression analysis, Gechert (2015) uses 104 studies to find STMs around 0.4, about half the size of other spending components. Alesina et al. (2017) do not find significant effects on GDP for transfer-led consolidations in a sample of OECD countries. Romer and Romer (2016) using a narrative approach to the changes in social security benefit increases in the United States document an immediate strong and positive response of private consumption, but with no significant effects on industrial production and employment. Similarly, Pennings (2021) finds a (cross-sectional) relative state transfer multiplier of 1.5 for permanent transfers and 1/3 for temporary transfers. Parraga-Rodriguez (2016, 2018) finds a social

[1] For example, the first phase of the Coronavirus Aid, Relief, and Economic Security (CARES) Act in the United States included one-time tax rebates to individuals, expanded unemployment benefits, and the Supplemental Nutrition Assistance Program (SNAP) social transfers that represented about 586 billion dollars, or 2.8 percent of the GDP of 2019. This social transfer amount is similar to that spent on the American Recovery and Reinvestment Act (ARRA) of 2009 (Oh and Reis, 2012).

[2] Throughout this paper, and unless noted otherwise, we therefore reserve the term STM to refer to the aggregate (as opposed to the local/regional) effect of a change in social transfers.

security benefit multiplier of 0.2 on impact and above 1 in the long-run in the US, and between 0 and 1 for a set of European economies. For Germany, Gechert et al. (2020) constructed a narrative dataset on the legal changes in social security benefits and contributions, finding an impact STM of 1.1 for social benefits and 0.4 for a reduction in contributions. For emerging markets, Egger et al. (2023) find a relative cross-sectional multiplier on cash transfers of 2.5 for Kenya. In Brazil, Cunha et al. (2022) find an implied GDP multiplier for Brazil's 2020 federal cash transfers targeted at vulnerable households in the range of 0.5-1.5. At the sub-national level, Feler et al. (2023) document a relative state transfer multiplier of 2.2, finding that states receiving 1 percent of GDP in extra transfers targeted to the poor grow 2.2 percent faster in the first year.

A widely used identification strategy in fiscal multipliers follows Blanchard and Perotti (2002) imposing timing restrictions by assuming that while government spending changes are allowed to contemporaneously affect economic activity within the quarter, it takes the government at least one quarter to respond to developments in the state of the economy. The lack of within quarter feedback effects into output may be unrealistic for some categories of social spending and thus, we take a series of additional steps to decrease endogeneity concerns. First, we exclude any automatic stabilizers like unemployment insurance spending from the social transfer metric because of their inherent automatic and rapid response to developments in the state of the economy (McKay and Reis, 2016; Di Maggio and Kermani, 2016; Galeano et al., 2021). Second, we estimate any residual of spending elasticity of output to create a cyclically adjusted measure of social spending. Finally, we instrument cumulative changes in social transfers at each time horizon $t + h$ using the residual at time t of a regression of changes in our cyclically adjusted measure of social spending on the lags of a long list of macroeconomic variables including the changes of social transfers, GDP, total primary spending, fiscal revenues, and central bank interest rate, before using this measure as the instrument of the cumulative changes in social transfers at each time horizon $t + h$ to build our impulse response functions in a local projections framework (Jorda, 2005; Stock and Watson, 2007). We additionally perform several other exercises to further reduce concerns about omitted variable bias and endogeneity of fixed effects on a dynamic panel framework. We find that the size of the STM is three times larger in Latin American countries than in developed economies. While the STM is on impact 0.3 in developed countries, it is 0.9 in Latin American economies. In line with existing empirical papers based on data for developed countries, both samples also show that the effect on output is mainly driven by private consumption, whereas private investment remains largely unchanged. We also find that while the macroeconomic impact of social transfers is important in the short- and medium-term, it tends to weaken in the long-term. This is the first paper to provide evidence on the size and mechanism behind the aggregate (national) STM for emerging markets.

Among the few existing papers in the STM literature, there is a strong consensus that social transfer shocks affect output mainly through consumption rather than through investment (Romer and Romer, 2016; Alesina et al., 2017; Parraga-Rodriguez, 2018; Gechert et al., 2020; Pennings, 2021). This empirical fact points out that the primary mechanism behind the social transfer shock occurs through the government allocation of funds to agents with a high marginal propensity to consume, consistent with a demand-side mechanism, rather than through supply-side channels. In this study, we provide novel stylized facts on the share of HtM agents and the share of social transfers reaching them using survey-based dataset from Global Findex. We identify HtM agents influenced by the work of Lusardi et al. (2011) as those who are not able to cope with a financial shock.[3] The recipients of social transfers are identified directly from Global Findex. Two findings stand out from several interesting ones.[4] First, the share of HtM agents is, on average, 23 percent in the sample of developed countries and 60 percent in the Latin American sample.[5] Second, the share of social transfers reaching HtM agents is, on average, 25 percent in the developed sample and 65 percent in the sample of Latin American countries. That is to say, the share of social transfers reaching HtM agents is mostly a reflection of the share of HtM agents, rather than the result of a particular social transfers targeting ability. This result suggests that, at least when including all types of social transfers, the assumption in structural models that social transfers only reach HtM agents (known as perfect targeting) does not seem to hold (Oh and Reis, 2012; Giambattista and Pennings, 2017). We also show that these empirical regularities equally hold for a sample of 99 developed and emerging countries. The stylized findings on the composition of HtM agents and the targeting effectiveness of social transfers across different groups of countries carries important implications for the analysis of STMs. Adding non-linear terms on the share of the HtM population to our baseline estimation shows a significantly larger STMs on impact for those countries with the largest shares of HtM households.

To account for the heterogenous role of those who can save and those who are constraint to consume what they earn, the theoretical literature has mainly relied on different variants of closed-economy two-agent New Keynesian (TANK) models which prompt consumption to play a dominant role in response to a social transfer shock (Monacelli and Perotti, 2011; Coenen et al., 2012; Giambattista and Pennings, 2017; Mehrotra, 2018; Faria-e-Castro, 2022).[6] The distinctive and es-

[3]As discussed in Kaplan et al. (2014), while the identification of HtM agents is different from those studies based on the agents' liquid wealth, the empirical evidence is notably similar in terms of the shares of population living HtM. This robust finding is also present in our study when relying on Global Findex. For example, for the United States, Kaplan et al. (2014) find a share of HtM ranging between 25 and 40, with their preferred estimate being one-third. Ours, using Global Findex, is 27 percent. Section 4 provides extensive evidence of these similarities.

[4]In light of the debate in developed countries about the so-called wealthy HtM individuals (i.e., those with significant amounts of illiquid assets like real estate properties, yet high marginal propensity to consume out of transitory changes in income), we find evidence that wealthy HtM individuals also exist in emerging markets. Yet, the HtM phenomenon in emerging markets is largely driven by poor HtM individuals.

[5]This evidence is also in line with well-established, more macro/aggregate, evidence that emerging market economies have less financial depth, intermediation, and development than their developed counterparts (e.g., King and Levine, 1993; Beck et al., 2000; Beck et al., 2007). More recent micro-based evidence from individual spending data and local-based experiments also supports, to different degrees of explicitness, the relevance of financial fragility on the marginal propensity to consume and on the size of local STMs (e.g., Haushofer and Shapiro, 2016; Egger et al., 2023; Pennings, 2021; Gerard et al., 2020).

[6]Heterogeneous agents models, including HANK, have recently been used to structurally estimate the macroeconomic effects of transfer payment to households with different MPCs, given that they capture more realistic income

sential elements of this family of models are the existence of two types of agents that differ in their access to financial markets coupled with a fiscal authority capable of redistributing funds between these two groups of individuals.[7] While unconstrained Ricardian agents have access to financial markets and are, thus, able to smooth consumption, constrained hand-to-mouth (HtM, hereafter) individuals consume their entire income in each period and, consequently, have a higher marginal propensity to consume. The government collects lump-sum taxes from the Ricardian agents to pay for government purchases and social transfers to individuals. Naturally, if social transfers only reached Ricardian agents or if there were no HtM individuals, the STM would be equal to zero. The key to deliver a positive STM relies on social transfers actually reaching HtM individuals (i.e., the social transfer shock needs to redistribute funds from low-to-high-marginal-propensity-to-consume agents) along with the existence of HtM agents (who help propagate the effect of the initial social transfer shock). Moreover, TANK models deliver STMs that are larger the higher the share of HtM agents in the population (which increases the average marginal propensity to consume of the economy) and the higher the share of social transfers reaching HtM agents (which increases the redistribution of funds from Ricardian to HtM agents). Among other relevant features, these models also allow monetary policy to be more or less accommodative (the zero lower bound being the extreme case of the former) and fiscal policy to vary the degree of persistence of government spending shocks.

When studying the key determinants affecting the size of STMs, existing papers have focused on the importance of the persistence of the social transfer shock (Coenen et al., 2012; Romer and Romer, 2016; Alesina et al., 2017; Gechert et al., 2020; Pennings, 2021) and on the magnifying role of the more accommodative monetary policy on the STM (Coenen et al., 2012; Romer and Romer, 2016; Giambattista and Pennings, 2017; Mehrotra, 2018). Despite the above-mentioned progress, to the best of our knowledge, no study has focused on how the heterogeneity in the share of HtM agents and in the share of social transfers reaching HtM agents affect the size of STMs. Existing quantitative papers estimating STMs for the United States (Giambattista and Pennings, 2017; Pennings, 2021) discipline the share of HtM agents to one-third based on Kaplan et al. (2014). Kaplan et al. (2014) relied on household surveys for the United States and eight other developed countries to measure the share of HtM agents based on liquid net worth, finding modest heterogeneity among developed countries.[8] Notably, no paper uses data to discipline the share of social transfers reaching HtM agents. We empirically document that social transfers reaching HtM agents is different from

risks and wealth distribution (Oh and Reis (2012), Hagedorn et al. (2019) - although both find relatively small quantitative transfers multiplier in HANK). Given the emergency response to the COVID-19 shock via transfer payments to households, heterogenous agent models, such as in Carroll et al., 2021; Bayer et al. (2023), estimated large targeted STM. STMs in response to the COVID-19 is outside the scope of this paper.

[7] The influential paper by Oh and Reis (2012) was the first to call attention to the need to have heterogeneous agents coupled with redistribution arguments to deliver a positive STM.

[8] Kaplan et al. (2014) find that the shares of HtM households (expressed in percentage terms) are as follows: Australia (19), Canada (30), France (21), Germany (32), Italy (24), Spain (20), United Kingdom (33), and United States (31).

1 or imperfectly targeted, even in developed countries. Our calibrated standard two-agent New Keynesian (TANK) model is able to match key STM regularities identified empirically. Moreover, we show that about 80-90 percent of the large difference in the size of STMs between Latin American and developed countries is explained by the higher share of financially constrained individuals who live HtM in the Latin American sample relative to the developed countries. This evidence on the quantitative effect of HtM arguments, coupled with the strong evidence supporting a larger share of HtM agents in emerging markets, suggests that a bigger STM may be expected for emerging market economies in general.

The rest of the paper proceeds as follows. Section 2 shows the empirical estimates of STMs for both the developed and the Latin American samples. Section 3 presents the TANK model. Section 4 provides evidence that the share of HtM agents and the share of social transfers actually reaching them in emerging markets are much larger than in developed economies. Section 5 shows the role of the share of HtMs on the STMs across countries. Section 6 shows that a standard calibrated TANK model is able to match key empirical regularities shown in Section 2 in terms of the size, main macroeconomic variables involved, and temporal profile of the STM for both the developed and Latin American samples. Section 7 offers some final thoughts.

2 Empirical evidence on the Social Transfer Multipliers

Expenditure in social transfers is defined as current transfers receivable by households intended to provide for the needs that arise from social risks—for example, sickness, unemployment, retirement, housing, education, or family circumstances. These benefits are payable in cash or in kind to protect the entire population or specific segments of it against certain social risks. In accounting terms, social benefits are the combination of expenditure in social security benefits, social assistance benefits, employment-related social benefits.[9] Social transfers comprise both ongoing social protection programs and emergency policy responses.[10] Ongoing social protection programs refer to the disbursement of government funds to individuals who meet certain eligibility criteria. The main categories include unemployment benefits (transfers to unemployed individuals), family programs (transfers essentially to the poor and most vulnerable households), and pensions (mainly transfers to individuals after retirement). Social transfers represent a large component of government spending comprising more than 50 percent of primary government spending in developed countries and about 40 percent in emerging markets. By and large, the largest category of social transfers spending is

[9]It is important to note that not all social benefits as defined as an expense item. Social benefits exclude the payment of pensions and other retirement benefits through employment-related social schemes, which are recorded as reductions in liabilities. Additionally, goods and services produced by the government and transferred to households are expense transactions not classified as social benefits. Instead, the expense transactions are recorded as production expenses as part of the compensation of employees, use of goods and services, and consumption of fixed capital, as appropriate.

[10]This paragraph significantly relies on Galeano et al. (2021). See their paper for a detailed discussion of social transfers basic trends, composition, rigidity, and business cyclical aspects of social transfers.

pensions (accounting, on average, for more than 75 percent of social transfers), followed by family programs (about 20 percent, on average). Interestingly, in contrast to the emerging world's long history of social protection in terms of social security and the most recent wave of family programs, unemployment insurance programs are rare in emerging countries (they simply do not exist or, if they do, they have negligible coverage).

As the most important component in our Social Transfer's measure, spending on pensions accounts for more than half of social benefit expense in arguably all countries. According to the Government Finance Statistics (GFS) project by the IMF, social security benefits expenses represented, on average, 66 percent of total social benefits expense in countries in our sample for which disaggregated data is available in 2022. This figure can range from as high as 82 percent in Sweden to as low as 55 percent in the UK.

Pension types can be classified into one of three categories: first-tier (mandatory and independent of past earnings), second-tier (mandatory and earnings related) or third-tier (voluntary, earnings-related). The first-tier is public, the third private, and the second could be public, private, or a mix. The second-tier often offers a defined-benefit or defined-contribution regimes, or a combination of the two. In most cases, the former is administered by the public sector, and the latter by the private sector, although this is not necessarily the case.

Naturally, in this paper, we focus on the public component of pensions. One classification of changes in public pension spending is that of parametric versus structural reforms (Clement, 2014). Examples of the former include, but are not limited to, changes in the legal minimum retirement age, contribution rates, incentives for deferred retirement, the number of years of contribution needed, information on benefits of delayed retirement, benefits indexation rules, automatic enrollment, pension access to certain population groups that have typically been left out, and changes in the basis of calculation of benefits. Automatism itself can be seen as a parametric change, allowing the system to automatically adjust to certain changes in the environment.

Structural reforms have to do with changes in the relative importance of different types of pension schemes, such as privatizations, defined-benefit vs defined-contribution, pay-as-you-go versus funding, etc. Clement (2014) states that the most important structural reforms in the last four decades have been moving from a mostly PAYG, defined-benefit scheme administered by the public sector to a system with mostly fully funded, privately managed- defined-contribution schemes. There were also introductions of benefits destined to tackle poverty in old age, such as noncontributory, universal, social pensions.

Both parametric and structural reforms appear mostly as a response to demographic trends, or policies that aim to address the sustainability of the programs in response to these trends. The OECD (2021) estimated that the size of the working-age population (ages 20-64) is expected to decline by more than 25 percent by 2060 in most OECD countries, and the ratio of persons aged +65 to those of working age would nearly double by 2016. Other sources of change include socioeconomic and attitudinal changes such as those in marriage decisions, the changing role of women in the labor market affecting the number of people contributing to the system and eventually the recipients of pensions, or the changing nature of job careers, making individuals stay in school longer and enter the labor force later, resulting in shorter labor careers. As a response, the average normal retirement age in OECD countries has been increasing and is expected to increase by about 2 years by the mid-2060s, and contribution rate increases have been implemented by both industrial and developing countries (latest examples include, but are not limited to, Ireland in 2022 and 2024, Australia in 2023, Uruguay in 2023, Spain in 2022 and 2023, Mexico in 2020 and 2021).

Regarding the indexation of benefits, the public component of pensions is usually tied to measures of minimum wage, inflation, average wage, etc., to ensure a certain minimum purchasing power. Thus, any changes in these variables (given by endogenous or exogenous factors) will translate into changes in the amount of pension spending. In other countries, such as Argentina, increases are discretionary and determined by national decree.

While changes implemented in industrial countries, facing increases in life expectancy, are focused on improving the sustainability of their pension systems while maintaining adequacy, developing economies face a slightly different challenge, trying to improve coverage and pension adequacy while maintaining sustainability in a context of a younger population with falling but still relatively high fertility rates (Clement, 2014).

Given the importance of this social security spending in households' budgets, many of the changes necessary to sustain the programs are challenging to implement in reality and face considerable pushback. At the same time, political moves and populism play a significant role in some of the shocks to public spending in these categories, so election timing probably needs to be taken into consideration as a time with increases in these categories.

2.1 Data

This section estimates STMs using unbalanced quarterly data for the first quarter of 1960 through the fourth quarter of 2019 for six Latin American countries (Argentina, Brazil, Chile, Colombia, Mexico, and Peru) and 17 developed countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Norway, Portugal, Spain, Sweden, United Kingdom, and United States).[11] Beyond real output growth and the growth rate of real social spending, growth of real total primary spending, growth of real fiscal revenues, changes in central bank interest rates, and inflation are also used as controls in our regression analysis. Summary statistics of these variables are provided in Table 1.

TABLE 1

[11]See Appendix 1 for description of data definitions, sources, and time coverage for each country.

Figure 1 provides scatter plots of the change in total social transfers as a share of GDP against real GDP growth for all the countries in the sample as well as dividing between advanced and emerging markets. While the scatter plots show a weak positive correlation for the aggregate, we already observe a larger positive relationship among our LAC emerging markets than among advanced economies.

FIGURE 1

2.2 Methodology and identification strategy

In our baseline regression we use the well-known Blanchard and Perotti (2002) (BP henceforth) identification strategy that imposes timing restrictions by assuming that while government spending changes are allowed to contemporaneously affect economic activity (i.e., within the quarter), it takes the government at least one quarter to respond to developments in the state of the economy (e.g., Fatás and Mihov (2003), Galí et al. (2007), Corsetti et al. (2012), Ilzetzki et al. (2013), Huidrom et al. (2020)). We estimate the effect of innovations of social transfer shocks on economic growth using the single-equation approach proposed by Jorda (2005) and Stock and Watson (2007), which is based on linear local projections (LP). The use of LP provides several advantages over the traditional structural vector autoregressive (SVAR) methodology. Specifically, LP (i) can be estimated by single-regression techniques, (ii) are more robust to potential misspecifications, and (iii) can easily accommodate non-linear specifications that may be impractical in a multivariate SVAR context (a feature that proves to be crucial in this paper).[12]

Causality claims with a clean identification strategy is traditionally the most challenging part of empirical studies looking at fiscal incidence. While we take direct steps to deal with omitted variable bias or anticipation effects, our approach requires exogenous instruments in the contemporaneous (same quarter) relationship between transfer spending and economic growth. In this case contemporaneous cyclicality of spending is our biggest enemy. The procyclical fiscal policy found in the literature among emerging markets could positively bias STMs among these countries.[13]

Meanwhile, mild countercyclical policies employed in OECD countries could downward bias STMs estimates for these economies. Thus our main identification efforts are dedicated to clean any traces of contemporaneous cyclicality in social transfers leaving unanticipated and exogenous within-the-same-quarter social transfer shocks for use in the regression analysis.

Our empirical strategy follows a three-step procedure. First, we turn to the cyclical properties

[12]We should note that Jorda's LP method does not consistently dominate the standard SVAR method for calculating impulse responses of endogenous variables with contemporaneous effects. Since Jorda's LP does not impose any restrictions linking the impulse responses at h and h + 1, estimates can display an erratic behavior due to the loss of efficiency. Additionally, the impulse responses sometimes display oscillations at longer horizons (Ramey, 2016). For these reasons, and to err on the safe side, we report estimates up to 8 quarters after social transfer shocks.

[13]See Frankel, Vegh, and Vuletin (2013) for an updated look at the cyclicality of emerging and advanced economies.

of the different components of social spending. We note that in terms of their short-term fluctuating nature, unemployment insurance spending is, by design, countercyclical (even at the quarterly frequency!).[14] On the other hand, pensions and family programs spending tend to be more rigid and slow-moving in nature and are mainly driven by demographic and structural deep-rooted social problems, respectively. It is important to note that we are not negating the potential cyclicality of pensions and other social security components. As discussed in Galeano et al. (2021), there is evidence of procyclicality rooted in these spending components but, importantly for us, this cyclicality tends to be slow moving thus making this type of spending acyclical in the short run.[15] We, thus, clean our measure of social transfers from countercyclical automatic stabilizers like unemployment insurance because of its inherent automatic and rapid response to developments in the state of the economy (McKay and Reis, 2016; Di Maggio and Kermani, 2016; Galeano et al., 2021).[16] Recognizing that there may still be some within-quarter cyclicality embedded in the new measure, we estimate the output elasticity of expenditure by country and create a cyclically adjusted measure of social spending. Finally and similarly to BP, we clean our measure from potential anticipated effects by using the residuals of the following regression as our social transfer shocks:

$$\begin{aligned}\Delta ST_{i,t}^{ca,\ wo\ as} = \; & \sum_{l=1}^{L} \varsigma_l \Delta Y_{i,t-l} + \sum_{l=1}^{L} \psi_l \Delta ST_{i,t-l}^{ca,\ wo\ as} + \sum_{l=1}^{L} \eta_l \Delta G_{i,t-l} + \sum_{l=1}^{L} \zeta_l \Delta R_{i,t-l} + \\ & + \sum_{l=1}^{L} \gamma_l Inf_{i,t-l} + \sum_{l=1}^{L} \xi_l \Delta int_{i,t-l} + \varepsilon_{i,t}^{ST\ ca,\ wo\ as}\end{aligned} \tag{1}$$

for each country i, where $\Delta X_{i,t} = (X_{i,t} - X_{i,t-1})/Y_{i,t-1}$ and X being the cyclically adjusted real social transfers excluding automatic stabilizers (i.e. unemployment insurance) spending component ($ST^{\ ca,\ wo\ as}$), real GDP (Y), real total primary spending (G), real fiscal revenues (R), or CPI Inflation (Inf); and int is the central bank interest rates.[17]

Once we identify the unanticipated social in our cyclically adjusted transfer shocks excluding the unemployment insurance spending component $\varepsilon^{ST\ ca,\ wo\ as}$, we use a local projections approach to find a cumulative impulse response function (IRF), representing the STM at different time horizons. This methodology allows us to directly project the behavioral reaction of GDP to the unanticipated

[14]In fact, the contemporaneous correlation between quarterly changes of real GDP and real unemployment insurance spending is -0.23 (statistically significant). Pennings (2021) also provides some similar evidence for the United States.

[15]Furthermore, the contemporaneous correlation between quarterly changes of real GDP and real pensions and family programs spending is 0.09 (statistically not significant).

[16]Interestingly, given the relatively small share of unemployment insurance spending on total social transfers in Latin American countries, we cannot reject the null hypothesis that the contemporaneous correlation between quarterly changes of real GDP and real social transfers excluding (or including) unemployment insurance spending is 0.09 (0.06); in both cases statistically not significant.

[17]The number of lags $L = 4$ is determined through log-likelihood ratio information criterion tests (see Hamilton (1994), pages 295-296). The same lag structure was recommended when using the Akaike Information Criterion (AIC) or the Hannan-Quinn information criterion (HQC).

social transfer shocks by computing estimates of the h-step-ahead cumulative average treatment effect on the GDP variable.[18]

A common problem in the literature is matching the typical definition of a fiscal multiplier (i.e., total output change at step h divided by total expenditure change at step h) with the estimated steps of an IRF originated from an initial spending shock. To bypass this problem, we follow Ramey and Zubairy (2018) and use a two-step instrumental variable procedure. In the first stage, we find the predicted cumulative social transfers at each step h from the unanticipated social transfers shock excluding the unemployment insurance spending component in time t from the following regression:

$$\begin{aligned}\Delta ST_{i,t+h} = \quad & \xi_h \varepsilon_{i,t}^{ST\ ca,\ wo\ as} + \sum\nolimits_{l=0}^{h-1} f_{lh} \varepsilon_{i,t+h-l}^{ST\ ca,\ wo\ as} + \sum\nolimits_{l=1}^{L} k_l \Delta Y_{i,t-l} + \sum\nolimits_{l=1}^{L} m_l \Delta G_{i,t-l} + \\ & + \sum\nolimits_{l=1}^{L} \lambda_l \Delta R_{i,t-l} + \sum\nolimits_{l=1}^{L} \gamma_l Inf_{i,t-l} + \sum\nolimits_{l=1}^{L} \vartheta_l \Delta int_{i,t-l} + c_{i,h} + q_{t,h} + \upsilon_{i,t,h}\end{aligned} \tag{2}$$

where $c_{i,h}$ and $q_{t,h}$ represent country and time fixed effects, respectively.

In the second stage, we use the predicted values $\Delta \widehat{ST_{i,t+h}}$ from the previous expression to instrument the cumulative social transfers in a regression against GDP:

$$\begin{aligned}\Delta Y_{i,t+h} = \qquad & \beta_{1h}^{IV} \Delta \widehat{ST_{i,t+h}} + \sum_{l=0}^{h-1} w_{lh} \varepsilon_{i,t+h-l}^{ST} + \sum_{l=1}^{L} \sigma_l \Delta Y_{i,t-l} + \sum_{l=1}^{L} \eta_l \Delta G_{i,t-l} + \\ & + \sum_{l=1}^{L} \zeta_l \Delta R_{i,t-l} + \sum_{l=1}^{L} \gamma_l Inf_{i,t-l} + \sum_{l=1}^{L} \zeta_l \Delta int_{i,t-l} + c_{i,h} + q_{t,h} + \mu_{i,t,h}\end{aligned} \tag{3}$$

where $\Delta X_{i,t+h} = (X_{i,h} - X_{i,t-1})/Y_{i,t-1}$. We use Teulings and Zubanov (2014) bias correction by including social transfer shocks nested between times t and h as controls. Estimator β_{1h}^{IV} in specification (3) represents the impulse response at each step h. By construction, each step in specification (3) also gives us the cumulative multiplier defined as the accumulated output divided by the accumulated spending in social transfers. Standard errors are drawn from a two-way cluster-robust covariance matrix.

In our sensitivity analysis, we further perform two additional robustness checks. First, responding to potential endogenity in our dynamic panel arising from the correlation of our autoregressive terms and the errors, we apply the System-GMM estimator pioneered by Arellano and Bond in 1991. Since the Arellano-Bond method is used to estimate dynamic panel data models with fixed effects and endogenous regressors, it allows us to include our social transfer measure as a potentially endogneous regressor jointly with the lagged dependent variables. This method uses first-differencing

[18] This methodology provides a flexible alternative to VAR approaches. As described by Jorda (2005), linear projections can be estimated by simple regression techniques (IV in our case) and they are more robust to misspecification errors. Nonetheless, Ramey (2016) points out some limitations—e.g., impulse responses sometimes display oscillations at longer horizons (particularly after 16 quarters). Since, in this study, we are interested in the short- and medium-horizon effects of social transfers on output, we can safely disregard these drawbacks.

to eliminate the fixed effects and instrumental variables to address the endogeneity problem. The instruments are based on lagged values of the dependent variable and the predetermined or exogenous variables. Finally, we test that our estimates are not driven by a particular country or by a set of extreme outliers.

2.3 Empirical findings

While our ultimate target is to study the output effects of social transfer shocks in an impulse-response environment, we start by exploring the social transfer multipliers on impact (the equivalent of assuming h=0 in specification (3) for a series of different specifications. Beyond understanding the impact of social transfer spending on output, in this first pass we want to test the stability in our estimates across different models and thus ensure that our results are not sensitive to alternative specifications.[19]

TABLE 2

Column 1 in Table 2 reports the STMs based on a least squares dummy variable model (LSDV). In this case, we use the total real spending in social transfers as our dependent variable and we include country and time fixed effects as well as a full set of controls and their respective lags. Since by construction, each step in equation (3) also gives us the cumulative multiplier defined as the accumulated output divided by the accumulated spending in social transfers, we estimate a $.301 immediate increase in real output after a $1increase in real social transfer spending.[20] This estimate is significant at a 99 percent confidence interval. In column 2, we continue with the LSDV model but we now use our cyclically adjusted measure of real social transfer spending net of automatic stabilizers. The new STM estimate is very similar to the original specification. Here, on impact, real output increases by $0.299 for each $1 increase in real cyclically adjusted social transfers. Following the BP framework, Column 3 cleans our cyclically adjusted social transfers measure of any anticipated effect by fist running the regression specified in Eq. (1), and then uses the residuals as proxy for unanticipated shocks on social transfers. Again, our estimate remains consistent with an increase of $0.389 in real output per dollar increased in our social transfers shocks. To match the definition of the multiplier (total output change divided by total expenditure change), column

[19]We compared our identified exogenous transfer BP shocks with pension shocks identified by Romer and Romer (2016) for the US and Gechert et al. (2020) for Germany using a narrative approach. While interpreting these results, it's important to note that, although spending on pensions accounts for more than 50% of social spending, our social transfer shock is more broadly defined than just pensions; it also includes family programs and other transfers to households. For the US, the simple correlation of shocks was 0.60, with a regression correlation of 0.57 (statistically significant at 1%) and an R2 of 0.36, indicating strong alignment for several key narrative shocks. For Germany, the simple correlation was 0.46, with a regression correlation of 0.52 (statistically significant at 1%) and an R2 of 0.21. These results suggest a reasonable cross-validation of our BP shocks, supporting their robustness.

[20]Recall that the STM measures the effect of a $1 change in social transfers on the level of GDP. For example, a STM of 0.7 indicates that an increase in social transfers of $1 increases GDP by $0.7.

4 shows the estimated coefficient using the instrumental variable (IV) framework represented by equations (2) and (3). Again, the coefficient remains stable with an increase of \$0.366 in real output per dollar increased in total social transfers spending, consistent with the meta-analysis of Gechert (2015).

While column 4 represents our preferred specification moving into the impulse response analysis, in a further effort to minimize endogeneity concerns, estimates in column 5 are obtained applying the System-GMM estimator pioneered by Arellano and Bond in 1991.[21] The Arellano-Bond method is used to estimate dynamic panel data models with fixed effects and endogenous regressors. It uses first-differencing to eliminate the fixed effects and instrumental variables to address the endogeneity problem. The instruments are based on lagged values of the dependent variable, the endogenous independent variables and the predetermined or exogenous variables. Since the standard first-differenced GMM estimator of Arellano and Bond (1991) has been found to have poor finite sample properties (in terms of bias and imprecision) in the case in which the series are highly persistent or if the variance of the individual specific effect is large relative to the variance of the error (see Blundell and Bond 1998).[22] We use the Arellano and Bover (1995) and Blundell and Bond (1998) system-GMM estimation instead.[23] System-GMM estimates of the STM remains close to previous values at \$0.272.

Finally, Tables A.5.1 and A.5.2 in the Appendix show that our results are not affected by outliers or lead by the effects of any single country. In table A.5.1, using our preferred BP IV specification, we winsorize the sample by dropping the 1, 2 and 3 percent of the tails on the dependent and independent variables. The estimates of these regressions show, if anything, a slight increase in our STM estimates and a decrease in the standard errors. Table A.5.2 and we show our estimates after dropping one country at a time to ensure that coefficients are not changed by any single country.

Our next goal in the analysis is to better understand the dynamic output effects of changes in social transfers. For that, we build impulse response functions based on the local projections methodology represented in equation (3). Figure 2 shows the cumulative effects on real output for 8 quarters following the shock in social transfers. The figure shows statistically significant cumulative STM peaking in the second quarter at around 64 cents output return per dollar spent. Beyond that point, the cumulative STM starts to decline and quickly becomes statistically insignificant.

[21] Given small differences in the estimates from System-GMM and the BP-IV specification, we use the later as our preferred specification given the risks of System-GMM to be over-identified and the tendency to suffer from weak instruments regardless of passing the standard tests. This may lead to downward bias in our estimates. Thus, we see System-GMM as a robustness check on the downward boundaries of our estimates.

[22] In such cases, the lagged levels of the series are only weakly correlated with subsequent first differences, thus leading to weak instruments. Instrument weakness, in turn, increases the variance of the coefficients and, in relatively small samples, is likely to generate biased estimates.

[23] Since a proliferation of instruments may overfit endogenous variables and lead to a loss of power, we restrict the maximum lag length of the lagged instruments to 5 and show that the results are not particularly sensitive to the choice of alternative maximum lag lengths. We also provide the relevant instrument weakness and over-identification tests.

FIGURE 2

Of course figure 2 averages STM across two very different sets of countries. As discussed in the introduction, emerging economies are structurally different from their advanced counterparts. Our next step in the analysis is to check if these structural differences affect the social transfer elasticities of output. To test this hypothesis we upgrade equation 3 to include a dummy interaction separating LAC economies from the rest.

$$\begin{aligned}\Delta Y_{i,t+h} = \quad & \beta_{1h}^{IV} \Delta \widehat{ST_{i,t+h}} + \beta_{2h}^{IV} \Delta \widehat{ST_{i,t+h}} \times LAC + \sum\nolimits_{l=0}^{h-1} w_{lh} \varepsilon_{i,t+h-l}^{ST} + \\ & + \sum\nolimits_{l=1}^{L} \sigma_l \Delta Y_{i,t-l} + \sum\nolimits_{l=1}^{L} \eta_l \Delta G_{i,t-l} + \sum\nolimits_{l=1}^{L} \zeta_l \Delta R_{i,t-l} + \\ & + \sum\nolimits_{l=1}^{L} \gamma_l Inf_{i,t-l} + \sum\nolimits_{l=1}^{L} \zeta_l \Delta int_{i,t-l} + c_{i,h} + q_{t,h} + \mu_{i,t,h}\end{aligned} \tag{4}$$

where LAC is a dummy variable equal to one if the country belongs to the Latin American sample and zero otherwise. Estimators β_{1h}^{IV} and β_{2h}^{IV} in specification (4) represent the impulse response at each step h. Given our non-linear approach, the STM for a Latin American country would be determined by $\beta_{1h}^{IV} + \beta_{2h}^{IV}$, while for a advanced economy, by β_{1h}^{IV}. Panels A and B in Figure 3 show the size of STMs in developed (blue color) and Latin American (red color) countries, respectively.

Looking at our results, the size of the STM is much larger in Latin American countries than in developed economies, particularly in the short- and medium-term. While the STM in developed countries is 0.3 (t=2.0) on impact, it is 0.9 (t=3.8), in Latin American economies.[24] In both sets of countries, the peak is reached after one quarter, coming to 0.5 (t=1.5) and 1.1 (t=2.6) in the developed and Latin American sets, respectively. After the first quarter, the output effects tend to decrease. In other words, while the temporal profile of the STM is similar in both set of countries, the size of the STM in Latin American countries is about three times larger during the short- and medium-term. The novel evidence of such large STM on a set of emerging markets –Latin American countries in this case– contrasts sharply with the more modest size of the STM obtained in developed economies. It is worth noting that the size of the STM for developed countries is similar to previous country-specific and panel-data-based empirical findings (e.g., Gechert, 2015; Romer and Romer, 2016; Alesina et al, 2017; Pennings, 2021).

FIGURE 3

[24] It is worth noting that if one had not excluded the unemployment insurance spending component from specifications (2) and (3), the estimated STM would have been slightly lower, especially for developed countries (STM would have been 0.25 instead of 0.3). This upward bias, especially for the of group of countries with a relatively large presence of unemployment insurance mechanisms, would have wrongfully indicated that the impact of social transfers has less of a positive impact on the economy because of the automatic (and countercyclical!) within the quarter nature of this shock absorber program.

As it has been common in this literature, we now analyze which are the main macroeconomic variables involved behind the findings of Panels A and B in Figure 3. Panels C and D in Figure 3 show multiplier estimates, now measuring the effect of social transfers on private consumption. Panels E and F show similar multiplier estimates focusing on the impact on private investment.[25] The empirical findings are quite clear: the output effect observed in Panels A and B are driven by the response of consumption (Panels C and D) as opposed to the statistically insignificant response of investment (Panels E and F). This is true for both developed and Latin American countries. While there is no previous empirical evidence for emerging markets in regard to the relative response in consumption and investment to a social transfers shock, the response estimated for developed countries matches that of previous studies.

Lastly, as the shock persistence has played a role in the literature in explaining the heterogeneity of the size of the multipliers (Coenen et al, 2012; Romer and Romer, 2016; Alesina et al., 2017; Gechert et al., 2020; Pennings, 2021), we estimate autoregressive social transfers growth regressions with a time trend for each country. We find a median autoregressive point estimate of the shock persistence (ρ) of 0.86 for the developed countries and 0.84 for Latin American countries. Moreover, we cannot reject the null hypothesis that the estimated shock persistence for these groups of countries are statistically the same. So if not persistence, what is driving this significant differences in STMs across emerging and developed economies? We argue that structural differences in the socio-economic composition of households across these groups of countries can largely explain this puzzle.

3 Model

To explain the different effects of social transfers across emerging and advanced economies, we start exploring the effects of social transfers on output in a closed-economy two-agent New Keynesian (TANK) model with two types of agents that differ in their access to financial markets and, therefore, have different marginal propensity to consume. Subsections 3.1 to 3.5 present the model. We follow the Giambattista and Pennings (2017) version of the TANK model very closely. Subsection 3.6 discusses the link between the share of HtM agents and the share of social transfers reaching them which, in turn, helps determine the degree of social transfers targeting. Lastly, Subsection 3.7 shows the STM analytical result of a simplified version of the model which highlights the most salient determinants affecting the size of the STM, including the role played by the share of HtM agents and the share of social transfers reaching them.

[25] These multipliers were estimated the same way as described above for the output multiplier–just changing the dependent variable.

3.1 The households' problem

There are two types of households: a Ricardian household, and a HtM household, with population shares $(1-\alpha)$ and α, respectively.

3.1.1 The Ricardian household's problem

There is a unit mass of individuals, $i \in [0,1]$, within the Ricardian household (agent 1). These individuals supply differentiated labor inputs to intermediate-goods producers and only differ in their ability to change their nominal wage each period (as wages are sticky à la Calvo). The Ricardian household has access to buy/sell non-contingent bonds in the financial markets (which allows its members to smooth consumption over time) and owns the capital in the economy (which is rented by its members to intermediate-goods firms). Consumption is equalized across individuals within the household due to the existence of Arrow securities (i.e., markets are complete within the household). Each individual at the Ricardian household solves the following problem:

$$\underset{c_{1,t},b_t,I_t,L_{1,t}(i)}{Max} \; E_0 \sum_{t=0}^{\infty} \beta^t \left[\ln\left(c_{1,t}\right) - \frac{L_{1,t}(i)^{1+\varphi}}{1+\varphi} \right], \tag{5}$$

subject to the following budget, capital accumulation, and labor demand constraints:

$$c_{1,t} + I_t + b_t = w_{1,t}(i)L_{1,t}(i) + MPK_t K_{t-1} + \left(R_{t-1}/\pi_t\right) b_{t-1} + \Pi_t - Tax_{1,t} + (1-\theta)Tr_t, \tag{6}$$

$$K_t = (1-\delta)K_{t-1} + \left[1 - S\left(I_t/I_{t-1}\right)\right] I_t, \tag{7}$$

$$L_{1,t}(i) = \left(W_{1,t}^*(i)/W_{1,t}\right)^{-\varepsilon_w} L_{1,t}, \tag{8}$$

where β is the intertemporal discount factor, c_t is real consumption, $L_t(i)$ is desired labor hours, φ^{-1} is the Frisch elasticity of the labor supply, I_t is investment, $-b_t$ is real debt, real wages are defined as $w_t(i) = W_t(i)/P_t$, MPK_t is the real gross rate of return on capital, R_{t-1}/π_t is the real interest rate, Π_t are profits from retailers, ε_w is the sticky wage elasticity, $Tax_{1,t}$ is the lump-sum tax paid to the government, Tr_t are the lump-sum social transfers received from the government by both households, $\theta \in [0,1]$ captures the share of social transfers reaching the HtM household, and, consequently, $(1-\theta)$ identifies the share of social transfers "leaking out" to the Ricardian household. If $\theta < 1$, then part of the lump-sum taxes paid by the Ricardian household comes back, also in a lump-sum manner, in the form of social transfers. It is also assumed that the capital adjustment cost follows the expression $S(I_t/I_{t-1})$, where $S(1) = S'(1) = 0$ and $S''(1) > 0$ in steady-state.

3.1.2 The HtM household's problem

There is a unit mass of individuals, $i \in [0,1]$, within the HtM household (agent 2). Unlike the Ricardian household, the HtM household is financially constrained (i.e., it cannot lend or borrow) and, consequently, it consumes its entire income each period. Each individual at the HtM household solves the following problem:

$$\underset{c_{2,t},L_{2,t}(i)}{Max} \; E_0 \sum_{t=0}^{\infty} \beta^t \left[\ln(c_{2,t}) - \frac{L_{2,t}(i)^{1+\varphi}}{1+\varphi} \right], \tag{9}$$

subject to the following budget and labor demand constraints:

$$c_{2,t} = w_{2,t}(i) L_{2,t}(i) + \theta Tr_t, \tag{10}$$

$$L_{2,t}(i) = \left(W^*_{2,t}(i)/W_{2,t} \right)^{-\varepsilon_w} L_{2,t}. \tag{11}$$

where, as previously explained, $\theta \in [0,1]$ captures the share of social transfers reaching the HtM household. On one extreme, when $\theta = 1$, all social transfers reach HtM agents and there are no social transfers "leaking out" to the Ricardian individuals. On the other extreme, when $\theta = 0$, no social transfers reach HtM individuals and all social transfers "leak out" to the Ricardian agents.

3.2 The firms' problem and sticky prices

There is a continuum unit measure of competitive intermediate-goods producers that rent capital from the Ricardian household and hire differentiated labor inputs from both Ricardian and HtM households, aggregating labor through a Cobb-Douglas production function $Y_t = K_t^{\mu} L_t^{1-\mu}$, where $L_t = L_{1,t}^{1-\alpha} L_{2,t}^{\alpha}$.[26] Retailers convert intermediate goods into final goods. Final output, Y_t^f, is produced by a continuum unit of retailers, l, who buy differentiated intermediate goods, Y_t, at price P^{int} in a competitive market, differentiate it at no cost, and sell a variety of final output, $Y_{l,t}$, at price $P_{l,t}$. Aggregate final output and prices are $Y_t^f = (\int_0^1 Y_{l,t}^{\frac{\sigma-1}{\sigma}} dl)^{\frac{\sigma}{\sigma-1}}$ and $P_t = (\int_0^1 P_{l,t}^{1-\sigma} dl)^{\frac{1}{1-\sigma}}$, where $\sigma > 1$ is the elasticity of substitution among varieties. Each retailer takes into account that it may not be able to change their price with probability γ_p when choosing the optimal price. Then prices are sticky à la Calvo and retailers face a downward sloping demand curve for their variety. This optimization problem leads to a standard New Keynesian Phillips curve $\hat{\pi}_t = \beta E_t \hat{\pi}_{t+1} - \kappa \hat{X}_t$, where a hat ($\wedge$) denotes a log deviation from steady-state. Variables π and $X = \sigma/(\sigma-1)$ represent the inflation rate and average mark-up. The parameter $\kappa = (1-\gamma_p)(1-\beta\gamma_p)/\gamma_p$ captures the slope of the Phillips curve that determines the responsiveness of inflation and output to demand shocks. The higher the price stickiness (i.e., the larger γ_p) the more firms are not able to change prices to the desired level and, therefore, demand shocks generate a larger response on output. When prices are flexible (i.e., $\gamma_p = 0$ or $\kappa \to \infty$), demand shocks only affect prices.

The relative price of intermediate goods is defined as the inverse of the retailer's average markup, $P_t^{int}/P_t = 1/X_t$. Then, the marginal product of labor and capital in terms of intermediate goods

[26] Giambatista and Pennings (2017) show in their Online Appendix 2.1 that when labor across Ricardian and HtM households are perfect substitutes and also coupled with the existence of a labor union, as in Galí et al (2007), the exact same allocations and multipliers are achieved as in the Cobb-Douglas specification. See Giambatista and Pennings (2017) for further details of this equivalence.

must be divided by the markup to generate the real marginal product.[27] Aggregate real wages are then given by $w_{1t} = (1-\alpha)(1-\mu)\,(1/X_t)\,(Y_t/L_{1,t})$ and $w_{2t} = \alpha(1-\mu)\,(1/X_t)\,(Y_t/L_{2,t})$.

In steady state, the HtM household receives a share α of labor income, due to the Cobb-Douglas specification. In order to simplify the steady state, it is assumed that the HtM household receives a transfer α of capital income and retailer's profits and pays a share α of government spending. Therefore, the HtM household accounts for a share α of total consumption.

3.3 Sticky wages

Workers are able to set their wages at a steady-state markup above their marginal rate of substitution $\mu_w = \epsilon_w/(\epsilon_w - 1)$, which implies that individuals have market power in their labor supply decisions. The labor supply of Ricardian and HtM households are composites of differentiated labor inputs: $L_{1,t} = \int_0^1 L_{1,t}(i)di$ and $L_{2,t} = \int_0^1 L_{2,t}(i)di$, respectively. Each individual of the Ricardian and HtM households can reset their nominal wage with constant probability $1-\gamma_w$ in each period. Hence, the (nominal) wage decision of a HtM member i at time $t=0$ is to choose $W^*_{2,0}(i)$ to maximize (9) subject to (11) and other constraints, taking a lower adjusted discount factor $\beta_2 = \gamma_w\beta$ which incorporates the fact that $W^*_{2,0}(i)$ can be reset in the future. The problem is analogous for the Ricardian individuals. This optimization problem leads to a New Keynesian wage Phillips curve $\hat{\pi}^w_{k,t} = \beta E_t \hat{\pi}^w_{k,t+1} - \lambda\hat{\mu}^w_{i,t}$, where $\lambda = (1-\gamma_w)(1-\gamma_w\beta)/\gamma_w(1+\varphi\epsilon)$ is the slope of the wage Phillips curve that determines the reaction of wage inflation (and then labor income) to demand shocks, $k = 1,2$.

3.4 Monetary policy

The Central Bank follows (in a log-linearized form) a Taylor rule with interest rate smoothing (ϕ_R) that reacts to deviations of inflation (ϕ_π) and output (ϕ_Y) from steady state:

$$\hat{R}_t = \phi_R\hat{R}_{t-1} + (1-\phi_R)(\phi_\pi\hat{\pi}_t + \phi_Y\hat{Y}_t), \tag{12}$$

where $\hat{R}_t = lnR_t - lnR_{ss}$ is the log-deviation of the gross nominal interest rate from steady state.

3.5 Fiscal policy

The government runs a balanced budget such that unproductive government purchases and social transfers are financed through lump-sum taxes on the Ricardian agents each period:

$$Tax_{1,t} = Tr_t + G_t. \tag{13}$$

[27] Deviations of Y_t^f from Y_t are second order in the neighborhood of the steady state, and so in the first-order approximation we have $Y_t^f = Y_t$.

As taxes are levied on the unconstrained agents, the timing of the taxes does not affect the multiplier due to Ricardian equivalence. The paths for $\hat{Tr}_t$ and $\hat{G}_t$ (where a hat ($\wedge$) for taxes, social transfers, and government purchases denotes a deviation from steady-state as a share of GDP) are exogenous and follow an AR(1) process $\hat{Tr}_{t+1} = \rho \hat{Tr}_t + e_{Tr,t+1}$ and $\hat{G}_{t+1} = \rho \hat{G}_t + e_{G,t+1}$ where $e_{Tr,t+1}$ and $e_{G,t+1}$ are a zero-mean i.i.d shock and ρ captures the persistence of the spending shocks. The model is closed by the standard aggregate resource constraint $Y_t = c_{1,t} + c_{2,t} + I_t + G_t$.

3.6 Social transfers targeting

A key aspect of the model is that the marginal propensity to consume of HtM agents (who are financially constrained and cannot lend or borrow) is larger than that of Ricardian agents (who have access to financial markets). This difference makes the fiscal allocation of social transfers between these two types of agents of special relevance and it is captured in the model by the parameter $\theta \in [0, 1]$. The larger the θ, the larger the share of social transfers reaching the HtM agents (see equation 10) and the lower the "leak out" to the Ricardian agents (see equation 6).

Interestingly, the parameter θ does not differentiate whether the social transfers actually reach HtM agents as the result of (i) a special effort by the fiscal authority (either discretionary and/or in terms of social transfer design) to particularly target those HtM agents as opposed to Ricardian agents or, rather, (ii) as the result of the mere existence and representation of HtM individuals in the population (e.g., in an economy largely populated by HtM agents it should be, in principle, quite easy to reach them extensively even without any targeted effort). For this purpose, we decompose θ into two components. One component aims at measuring the social transfers targeting (STT, hereafter) effort, which is defined as the ability to reach HtM agents beyond their share of the population α. That is to say, $STT \equiv \theta - \alpha$. A second component captures the share of HtM agents in the population (captured by parameter α). For example, a high value of θ (e.g., $\theta = 0.8$) could reflect a high prevalence of HtM agents (e.g., $\alpha = 0.8$) coupled with zero targeting (i.e., $STT = 0$) or, on the other hand, be the result of a low prevalence of HtM agents (e.g., $\alpha = 0.2$) along with an important targeting effort in identifying and reaching HtM agents (e.g., $STT = 0.6$). Moreover, social transfers targeting could, in principle, be "misdirected" showing a negative impact in terms of its targeting (i.e., $STT < 0$) when $\alpha > \theta$.

While through the lens of the TANK model, understanding the driving forces behind θ (either the fiscal effort in targeting or the result of a larger prevalence of HtM agents) does not seem to be of particular interest, this distinction is relevant both from a conceptual and fiscal policy point of view. While HtM agents' prevalence, α, is a structural parameter considered to be outside of the fiscal policy scope and more related to the degree of economic and financial development as well as economic policies in the financial sector, social transfers targeting (STT) is a key aspect of fiscal policy. Moreover, while a large θ driven by a large α (the extreme case being $\theta = \alpha$ and $STT = 0$), shows that social transfers are able to reach HtM agents "effortlessly" as a byproduct of having too many HtM individuals, a large θ driven by large efforts in social transfers targeting (i.e., $STT \equiv \theta - \alpha \gg 0$) indicates that a certain targeting effort is able to explicitly identify and reach those agents that are actually financially constrained. In fact, Section 4 shows cross-country evidence supporting that, when considering all types of social transfers, the share of social transfers reaching the HtM agents, θ, is, by and large, reflecting the prevalence of HtM agents, α, and less so social transfers targeting, STT.

3.7 Analytical STM from a simplified model

In this subsection, we show an analytical expression for the STM considering a simplified version of the model which makes the STM constant over time:[28]

$$STM \equiv \frac{dY}{dTr} = \theta \left[(1-\alpha) + \Gamma \frac{\kappa (\varphi + 1)}{(1-\rho\beta)} \right]^{-1} > 0 \tag{14}$$

where $\Gamma = [(1-\alpha)(\phi_\pi - \rho) / (1-\rho)] - [\alpha (1-\rho\beta) / \kappa] > 0$. From STM expression (14) it is straightforward to show that: (i) $dSTM/d\phi_\pi < 0$ (a larger ϕ_π makes Ricardian agents cut their consumption more as the real interest rate goes up), (ii) $dSTM/d\varphi^{-1} > 0$ (due to larger labor supply effects), (iii) $dSTM/d\rho < 0$ (because a lower ρ reduces the need of Ricardian agents to cut their consumption due to lower labor supply effects), (iv) $dSTM/d\gamma_p > 0$ (demand shocks have larger effects on output rather than on prices), (v) $dSTM/d\alpha > 0$ (mainly because a larger share of HtM agents, α, increase the average marginal propensity to consume of the economy), (vi) $dSTM/d\theta > 0$ (as social transfers particularly reach those HtM agents with high marginal propensity to consume).[29]

It is important to note that while having a larger share of HtM agents, α, or a bigger share of social transfers reaching the HtM agents, θ, increases the size of the STM, these increases are in and of itself associated with lower and higher levels of well-being, respectively. Why? Because a larger α points to more individuals not being able to smooth consumption, whereas a bigger θ depicts more social transfers being allocated to constrained individuals. In other words, while having a larger α amplifies the effect of a social transfer shock, it is not something that, naturally, should be commended as desirable.

[28] In particular, following Giambattista and Pennings (2017), it is assumed flexible wages ($\lambda \to \infty$), no capital ($\mu \to 0$), no steady state government spending ($G_{ss} = 0$), a simplified Taylor rule where nominal interest rates only respond to contemporaneous inflation ($\phi_R = 0$ and $\phi_Y = 0$), a wage subsidy in steady-state equal to $s_{ss} = X_{ss} - 1$, that the Taylor principle holds ($\phi_\pi > 1$), and that the HtM share is not too high ($\alpha < (2+\varphi)^{-1}$).

[29] It is worth noting that the empirical evidence obtained from properly adding interaction terms to empirical specification (3) with respect to country-varying variables ρ, α, and θ (see Sections 4 and 6 for measurement details) delivers the model-based sign estimates. Results are not shown for brevity.

4 The share of HtM individuals and the share of social transfer reaching them in data

Given the nature of our contribution, it is essential to be able to measure the share of HtM individuals, α, as well as the share of social transfers reaching them, θ. As discussed in the introduction, no paper disciplines the share of social transfers reaching HtM agents, θ, by data. It is generally assumed that social transfers solely reach HtM agents (i.e., $\theta = 1$), which is referred to as perfect social transfers targeting. Regarding the share of HtM agents, α, quantitative papers estimating STMs for the United States (Giambattista and Pennings, 2017; Pennings, 2021) discipline the share of HtM agents to one-third based on Kaplan et al. (2014). There have been two main strategies to identify HtM agents in the United States and other developed countries.

A first group of studies relies on survey data on household portfolios, with an emphasis on savings, net worth, and the liquidity of assets (e.g., Kaplan and Violante, 2014; Kaplan et al., 2014; Aguiar et al. 2020). In their seminal paper, Kaplan et al. (2014) find that between 25 and 40 percent of United States households are HtM, with their preferred estimate being one-third. Of all HtM households, about one-third are poor HtM (who hold little or no liquid wealth and no illiquid wealth) and two-thirds are wealthy HtM (who also hold little or no liquid wealth but have significant amounts of illiquid assets on their balance sheets, led by real estate properties). Just like the poor HtM households, wealthy HtM households have a large marginal propensity to consume out of small transitory income shocks (Kreiner et al. 2012; Broda and Parker, 2014; Jappelli and Pistaferri, 2014). Kaplan et al. (2014) also measure the shares of HtM households (expressed in percentage terms) for seven other developed countries finding modest heterogeneity among developed countries: Australia (19), Canada (30), France (21), Germany (32), Italy (24), Spain (20), and United Kingdom (33).

A second group of studies notes that holding assets is not the only means to cope with an unexpected financial shock. For example, individuals can also have access to credit or depend on the help of family and friends, among many other ways and margins to cope with a financial shock. These studies rely on surveys based on self-assessed measures of one's capacity to deal with financial shocks, regardless of whether the source of funds is the respondent's own assets, capacity to borrow, a network of family and friends, or something else (e.g., Johnson and Widdows, 1985; Worthington, 2004; Lusardi et al., 2011; Vandone et al., 2011; Brunetti et al., 2016). For example, in an influential paper, Lusardi et al. (2011) conducted a survey for a total of 9,148 individuals between the ages of 18 and 65 in the United States (where 2,148 individuals were surveyed) and other seven developed countries (with about 1,000 respondents per country) between June and September of 2009. Their essential strategy to identify financially fragile households relied on the following question: "How confident are you that you could come up with $2,000 if an unexpected need arose within the next month?" The $2,000 figure is chosen because it is of the same order of magnitude as the cost of an unanticipated major car repair, a large co-payment on a medical expense, a legal expense, or a home repair. For the survey conducted in the United States, 22 percent of households responded with certainty that they would not be able to come up with the funds and some other 28 percent reported that they would probably not be able to come up with those funds.

4.1 Database used

We use individual-level data from the World Bank's Global Findex which is a comprehensive database on how individuals 15 years old and above save, borrow, make payments, and manage financial risk. The data are collected in partnership with Gallup through nationally-representative surveys of more than 150,000 adults in over 140 economies (i.e., covers about 1,000 individuals per country as in Lusardi et al. 2011). Global Findex has been published every three years since 2011. We use its latest survey for the year 2017 because it allows one to identify all types of social transfers. Previous surveys of 2011 and 2014 did not include public pensions (this is of particular importance for our paper because the empirical evidence shown in Section 2 includes all types of social transfers). The country samples were designed to be nationally representative and were subsequently weighted to reflect each country's population. Given the focus on emerging markets and developed countries, we exclude from our descriptive analysis what the IMF classifies as "low-income developing countries." In total, we end up with 99 countries (including those 23 countries of our developed and Latin American sample). In particular, the Global Findex database includes two sets of questions to each surveyed individual which are essential for our purposes of measuring α and θ:

- Question FIN24 asks: "Now, imagine that you have an emergency and you need to pay [1/20 of GNI per capita in local currency]. Is it possible or not possible that you could come up with [1/20 of GNI per capita in local currency] within the next month?" The possible answers were "yes" or "no".[30] We use this question, like in the second group of studies which rely on self-assessed measures of capacity to deal with financial shocks, to calculate the share of HtM individuals, α.

- Questions FIN37 and FIN38 ask if "[i]n the past 12 months, have you, personally, received any financial support from the government? This money could include payments for educational or medical expenses, unemployment benefits, subsidy payments, or any kind of social benefits. Please do not include wages or any payments related to work" and "[i]n the past 12 months, have you, personally, received a pension from the government, military, or public sector?", respectively. The possible answers were "yes" or "no". We use these questions to identify the share of social transfers reaching HtM individuals, θ.

[30] In the case of the United States, this 1/20 of GNI per capita in local currency for the year 2017 was equivalent to 2,380 dollars which is very similar to Lusardi et al. (2011).

4.2 Share of HtM individuals is more than twice as large in emerging markets

Figure 4 shows the share of HtM individuals, α, in each country. Red bars depict emerging markets while blue bars indicate developed countries. For ease of reading, countries with labels correspond to those used in our sample of six Latin American and 17 developed ones. The visual impression is striking: a majority of blue bars lie to the left of the figure and the majority of red bars lie to the right (indicating a larger share of HtM individuals in emerging countries). In fact, the average share of HtM individuals is twice as large in emerging countries as in developed countries (47.5 percent vs. 23.8 percent, with a statistically significant difference). For our sample of six Latin American countries, the average share of HtM individuals is even larger, reaching 60 percent.[31]

FIGURE 4

While using a different period of coverage, measure, and identification strategy, this evidence seems to match fairly well that of country-specific studies. For example, for Mexico, we find that 72 percent of individuals are HtM and Cugat (2019) finds that for years 2016-2018 about 58 percent of Mexican households have no access to formal financial markets. For the United States, we find that 27 percent of individuals are HtM and Kaplan et al. (2014) find that for the period 1989-2010 between 25 and 40 percent of American households are HtM, with their preferred estimate being one-third. For Korea, we find that 20 percent of individuals are HtM and Song (2019) finds that for the period 2012-2017 between 25 and 30 percent of households are HtM. For Japan, we find that 18 percent of individuals are HtM and Hara et al. (2016) find, following Kaplan et al.'s (2014) approach, that the share of HtM is about 13 percent for the years 1989-2009.

Appendix 2 provides further evidence regarding key characteristics about the nature and main characteristics of HtM and non-HtM. First, it shows evidence that while a vast majority of non-HtM individuals in the developed world would rely on savings to cope with a financial shock, the top source of funding of individuals living in emerging markets would be aid from family, relatives, and friends. Furthermore, in both set of countries, few individuals would rely on selling assets for providing support, so illiquid wealth (such as real estate properties) does not seem to be important for dealing with a financial shock. Second, and using information on whether individuals have a standing property loan, there is strong evidence that wealthy HtM individuals are also present in emerging markets (and not solely in developed countries). Interestingly, yet not surprisingly, while wealthy HtM represent an important share of all HtM individuals in developed countries, it is less the case in emerging markets where the HtM phenomenon is largely driven by poor HtM individuals. Lastly, this appendix analyzes whether the capacity to deal with a financial shock varies across several plausible relevant economic and demographic, individual and household, characteristics. As

[31]It is worth noting that the Global Findex survey of 2014 would reach virtually identical results regarding the share of HtM individuals, α, with emerging (developed) countries showing slightly lower (higher) values of α, of about 2 percentage points.

in previous studies relying on data from developed countries, individuals living in households with higher income, greater educational attainment, male, and employed show a higher capacity to deal with a financial shock, both in developed and in emerging countries (with even similar predicting capacity values among these groups of countries).

4.3 Evidence on allocation of social transfers

Figure 5 shows the share of social transfers reaching HtM individuals, θ. This is the first study showing evidence about this very important aspect of social transfer fiscal policy.[32] There is a much larger share of social transfers reaching HtM individuals in emerging countries. In fact, the average share of social transfers reaching HtM individuals is about twice as large in emerging countries as it is in developed countries (45.7 percent vs. 23.4 percent, with a statistically significant difference). For our sample of six Latin American countries, the average share of social transfers reaching HtM individuals is even larger, achieving 64.6 percent.

FIGURE 5

Figure 6 shows the relationship between the share of HtM individuals, α, (x-axis), and the share of social transfers reaching HtM individuals, θ, (y-axis). Most countries, both developed and emerging, lie very closely to the 45 degree line, implying that the higher the share of HtM individuals, the higher the share of social transfers that reach HtM individuals.[33] Alternatively, Figure 7 shows the relationship between the share of HtM individuals, α, (x-axis), and social transfers targeting, STT, (y-axis), depicting no systematic relationship between STT (recall $STT \equiv \theta - \alpha$) and α.[34,35] In other words, when considering the universe of all types of social transfers, countries' ability to reach HtM individuals seems to mainly reflect the prevalence of HtM individuals, α, as opposed to a fiscal targeting effort aimed to reach HtM individuals beyond their population representation. Therefore, social transfers in emerging markets are able to reach those HtM individuals mainly because a large part of its population is in the HtM group as opposed to a particularly exceptional targeting of social transfers. The same lack of evidence of high-quality social transfers targeting holds also true in developed countries.

FIGURES 6 *AND* 7

[32]Naturally, there is a large related micro-literature focusing on how specific social programs can reach and impact vulnerable people based on their income levels, poverty status, and other socioeconomic/demographic aspects (e.g., Grosh, 1992; Gasparini et al., 2013; Cruces and Gasparini, 2012).

[33]In fact, and based on a simple regression of θ against α, we cannot reject the hypothesis that such a coefficient equals statistically one for the whole sample of countries (as well as for industrial and emerging markets separately).

[34]Based on a simple regression of STT against α, we cannot reject the hypothesis that such a coefficient equals statistically zero for the whole sample of countries (as well as for developed and emerging markets separately).

[35]Appendix 3 shows the share of HtM individuals (α), the share of social transfers reaching HtM individuals (θ), and the social transfers targeting (STT) for each of the 99 developed and emerging countries included in our sample.

5 Empirical Evidence on the role of HtM shares in STMs

Our theoretical model shows that the share of HtM individuals can have an important role driving the effectiveness and timing of STMs. Before testing the quantitative results of the TANK model against our empirical differences between emerging and advanced economies, we take advantage of the heterogeneity among HtM shares displayed by the countries in our sample to empirically test if social transfers have, indeed, non-linear effects on aggregate output. In order to conduct this test, we upgrade equation (3) with an interaction between our social transfer shock and the HtM of the country:

$$\begin{aligned}\Delta Y_{i,t+h} = \; & \beta_{1h}^{IV}\Delta\widehat{ST_{i,t+h}} + \beta_{2h}^{IV}\Delta\widehat{ST_{i,t+h}} \times HtM_i + \sum_{l=0}^{h-1} w_{lh}\varepsilon_{i,t+h-l}^{ST} + \\ & + \sum_{l=1}^{L}\sigma_l \Delta Y_{i,t-l} + \sum_{l=1}^{L}\eta_l \Delta G_{i,t-l} + \sum_{l=1}^{L}\zeta_l \Delta R_{i,t-l} + \\ & + \sum_{l=1}^{L}\gamma_l Inf_{i,t-l} + \sum_{l=1}^{L}\zeta_l \Delta int_{i,t-l} + c_{i,h} + q_{t,h} + \mu_{i,t,h}\end{aligned} \tag{15}$$

In this specification, we are provided with a continuous array of STM's in each step corresponding to each share of HtM ($STM_h = \hat{\beta}_{1h}^{IV} + \hat{\beta}_{2h}^{IV} \times HtM_i$). Building from $\hat{\beta}_{1h}^{IV}$ and $\hat{\beta}_{2h}^{IV}$. Figure 8 shows the estimated paths of cumulative STMs along different shares of HtM on impact (h=0) and 1 year after the shock (h=4).

FIGURE 8

Figure 8 showcases the non-linear nature of STMs over the share of HtM households. For relatively low shares of HtM households, the STMs are close to zero and statistically insignificant both on impact and after 1 year. For countries with HtM shares above 40 percent, STMs start to become large and statistically significant. Going back to our original empirical findings, the strong non-linear nature of STMs along the share of HtM can help explain differences between the emerging and advanced economies in our sample. At a 23 percent of HtM, the average value across our advanced economies, we find cumulative STMs of $0.3 and $0.25 on impact and after a year respectively. Both estimates are not statistically significant at a 90 percent confidence level. Meanwhile, at 60 percent of HtM, the average value for the LAC countries in our sample, cumulative STMs increase to $0.5 and $1.35 on impact and after 1 year respectively. Both estimates are significant at a 95 percent confidence level.[36]

[36] Using the GMM-IV specification we get slightly smaller but qualitatively similar results with statistically insignificant STMs for advanced economies and estimates around $0.3 and $0.1 on impact and after 1 year respectively and statistically significant STMs for LAC economies with cumulative STMs estimates around $0.5 and $1 on impact and after 1 year respectively

MAP 1

As shown in maps 1.A and 1.B, we can use our "local" non-linear estimates $\hat{\beta}^{IV}_{1h}$ and $\hat{\beta}^{IV}_{2h}$ to extrapolate STMs to a global sample of countries based on their HtM shares. In the maps, we can see higher STMs on impact and after 1 year in emerging markets, specially among some LAC and sub-Saharan economies.[37] While our theoretical framework details the mechanisms connecting HtM shares to the effectiveness and time profile of STMs, it may be argued that our empirical non-linear estimates could be arising from other underlying mechanisms which are just proxied by HtM shares. Two usual suspects, specially among emerging markets, are the degree of trade openness and the type of exchange rate regime (Ilzetzki, Mendoza, and Végh, 2013). To ensure that HtM shares are randomly distributed across these important dimensions, we estimate the product-moment correlation coefficient, ρ, between HtM and both the Forex Regime variable as well the openness variables using:

$$\hat{\rho} = \frac{\sum_{i=1}^{n} w_i \left(x_i - \bar{x}\right)\left(y_i - \bar{y}\right)}{\sqrt{\sum_{i=1}^{n} w_i \left(x_i - \bar{x}\right)^2}\sqrt{\sum_{i=1}^{n} w_i \left(y_i - \bar{y}\right)^2}} \tag{16}$$

With weights $w = 1$. Our unadjusted significance level is calculated as:

$$p = 2 * ttail\left(n-2, |\hat{\rho}|\sqrt{n-2}/\sqrt{1-\hat{\rho}^2}\right) \tag{17}$$

Panel A in Figure 9 shows the relationship between trade openness (TO), measured as total merchandise trade over GDP, and the share of HtM households. Both the scatter plot and the Pearson coefficient do not find any perceivable correlation between TO and HtM. Panel B in Figure 9 also fails to find any systemic relationship between HtM share and exchange rate regimes. Here, we follow Ilzetzki, Reinhart, and Rogoff (2021) in arranging exchange rate regimes in 4 categories in increasing degree of exchange rate flexibility from hard pegs (value of 1) to freely floating regimes (value of 4).

FIGURE 9

Table 3 finds insignificant correlation coefficients among HtM and the other variables when running a linear OLS regression. Table also shows very small correlation coefficients with their corresponding p-values.

TABLE 3

[37] Cumulative STMs for specific economies can be provided upon request

6 Quantitative results from the TANK model

With the ability to measure α and θ, we now proceed to solve the TANK model presented in Section 3 numerically in order to analyze the extent to which a standard calibrated TANK model is able to match key empirical regularities shown in Section 2 in terms of the size, main macroeconomic variables involved, and temporal profile of the STM for both the developed and the Latin American samples.[38] Initially, in our benchmark calibration, and in order to direct our attention to the role played by α and θ, we calibrate the rest of parameters based on values frequently used in the literature for developed countries. Later, we also allow other parameter values (other than α and θ) to be calibrated for Latin American countries and find, indeed, very similar results to our benchmark calibration due to the actual dominant role played by α and θ. Some parameter calibration values deserve special attention. A key mechanism in the literature on fiscal multipliers is the reaction of the nominal interest rate to inflation and output gaps by central banks (i.e., parameters ϕ_π and ϕ_Y in the Taylor rule of equation 12). We follow Iacoviello (2005) in choosing a value of $\phi_\pi = 1.27$, $\phi_Y = 0.13$, and $\phi_R = 0.73$. The persistence parameter $\rho = 0.86$ is based on our own estimates shown in Section 2. The rest of parameter values are selected as follows: Frisch elasticity $\varphi^{-1} = 1$ (as in Christiano et al., 2005), discount rate $\beta = 0.995$, Calvo probabilities $\gamma_p = \gamma_w = 0.75$ (from Barattieri et al., 2014), sticky wage elasticity $\varepsilon_w = 20.50$ (matching 5% unemployment rate), steady-state government purchases $G_{ss} = 0.20$ (from World Development Indicators), steady-state capital adjustment cost $S'' = 1.5$ (from Altig et al., 2011) as well as depreciation rate $\delta = 0.016$, average mark-up $X = 1.10$, and capital share $\mu = 0.30$ (in order to match K/Y from KLEMS). Measurement and sources of data regarding parameters α and θ were discussed in detail in Section 4. In particular, we take the average α and θ for each sample in the Latin American and developed groups (i.e., $\alpha_{Developed} = 0.23$, $\theta_{Developed} = 0.25$, $\alpha_{Latin\ America} = 0.60$, $\theta_{Latin\ America} = 0.65$).[39]

Before turning our attention to the differences between LAC and advanced economies as a group, Figure 10.A shows how the relationship between on-impact STMs for individual economies evolves along HtM shares closely following the implied theoretical slope. Additionally, Figure 10.B shows a strong country-specific correlation between the on impact STM empirical estimation of Eq. (15) and its corresponding model implied STM. The model implied STM are well within the 90 percent confidence intervals, with the exception of countries with the highest share of HtM in our sample (Mexico and Argentina). [40] Furthermore, the country specific on impact STM estimated via Eq. (15) match relatively well the limited STM available in the literature.[41]

[38]We would like to thank Steven Pennings for sharing the Dynare code from Giambattista and Pennings (2017).

[39]It is also worth noting that the standard deviation of α within each sample of countries is relatively low: 7 percent and 9 percent in Latin American and industrial countries, respectively. On the contrary, for the joint sample it is 17 percent. The equivalent percentages for θ are 7 and 10 for Latin American and industrial countries, respectively. On the contrary, for the joint sample it is 18 percent.

[40]This over-estimation decreases over time and may be associated with information rigidities not captured in the model and informal labor market dynamics that reduce the on impact MPC (Feler et al., 2023).

[41]As illustrated in Figure 10, both the NK model and the results from Equation (15) indicate low STMs for

FIGURE 10

Figure 11 compares STMs, on impact, from the calibrated TANK model (dotted bars) with the empirical estimates shown previously in Section 2 (solid bars). Panel A shows the size of STMs both for the developed and Latin American countries. Panel B presents the difference in STMs between these two groups. Panel A shows that the calibrated TANK model is largely able to account for the observed empirical evidence. The TANK model delivers much larger STMs for the Latin American sample than for the developed one. The quantitative STM delivered by the model on impact is 0.21 in developed countries and 0.92 in the Latin American sample. Notably, these results are well within the reported 90 percent statistical range associated with the empirical STM estimates which are associated with STM point estimates of 0.31 in developed countries and 0.90 in the Latin American sample.[42] As observed in the empirical estimates, most of the macroeconomic effect of the social transfer shock is driven by the reaction of private consumption as opposed to private investment.[43] In other words, much like the findings of papers focused on developed countries, the effect on output mainly occurs through consumption while private investment remains virtually unchanged. Panel B shows, now focusing on the difference in size of STMs, that findings from Panel A imply that the model also accounts for the observed differences between these two groups of countries. For example, the difference in the effect of social transfers on output based on the model is 0.71 (second dotted grey bar) which is well within the reported 90 percent statistical range associated with the empirical evidence of 0.58 (first solid grey bar).

FIGURE 11

Sweden and Norway (0.12 and 0.10, respectively, and not statistically significant), with HtM shares of 10% and 7%, respectively. Conversely, Greece and Portugal exhibit STMs more akin to those in Latin American countries (0.42 and 0.41, respectively, and statistically significant), with HtM shares of 44% and 43%, respectively, aligning with the findings in Parraga-Rodriguez (2016). When comparing individual STMs with those available in the literature, the on-impact STM for the US (0.27) aligns with the on-impact government transfer multiplier of 0.20 reported by Parraga-Rodriguez (2018) and the NK model-implied STMs from Pennings (2021) with constant interest rates and untargeted transfers (0.5). However, Parraga-Rodriguez (2018) documents a cumulative one-year STM of around 1, which increases over time. While our empirical results from Equation (15) show increasing STMs over time, for the US, this increase is only 0.30 and not significant. For Germany, we find an on-impact STM of 0.14, which is not statistically significant (with an HtM share of only 12%). Our results do not distinguish between pension contributions and pension benefits, making comparisons with Gechert et al. (2020) challenging. Gechert et al. document on-impact GDP responses of 0.4 for a reduction in contributions and 1.1 for benefit increases, noting different persistence and channels through which these shocks operate.

[42] As a reference, if one had used the usual assumption in the literature that social transfers only reach HtM agents, known as perfect social transfers targeting (i.e., $\theta = 1$), the implied quantitative STMs would have been much larger and disconnected with our empirical estimates. In particular, the quantitative STMs would have been 0.83 for the developed countries and 1.42 for the Latin American economies.

[43] Using these parameter values, our calibrated TANK model implies an aggregate marginal propensity to consume of 0.18 for developed economies and 0.79 for Latin American countries. This is the response of a one-time transfer shock in the model. These model-implied marginal propensity to consume are consistent with both household survey empirical estimates of 0.1-0.4 for developed economies (Carroll et al., 2014; Broda and Parker, 2014; Japelli and Pistaferri, 2014; Johnson et al., 2006) and the excess sensitivity of consumption to changes in disposable income computed using aggregate data for developing countries (Islamaj and Kose, 2016).

Four other aspects of the quantitative TANK model results are worth noting. First, the long-run multiplier is also about 4 times larger in Latin American countries (with a STM equal to 0.15) than in the developed sample (with a STM of 0.04).[44] Second, as shown in Figure 12, the model is also able to match quite well the temporal profile depicted in the empirical estimates of Section 2. In fact, the rank-correlations observed in GDP, consumption, and investment between the quantitative results of the model and the empirical estimates range between 0.73 and 0.95 (in all cases statistically significant). Panel A shows that the STM is, on impact, four times larger in Latin American countries than in developed economies. Panel B shows that private consumption increases in response to a positive social transfer shock (especially in Latin American countries) due to the redistribution of funds from low to high marginal propensity to consume households. Investment decreases in both developed and Latin American countries given that as inflation goes up, monetary policy reacts by increasing the real interest rate (i.e., $\phi_\pi > 1$). Inflation increases more in Latin American countries due to the greater change in aggregate demand (i.e., higher α) and, therefore, the larger the increase in the real interest rate, the larger the drop in investment.

FIGURE 12

Third, we now analyze how much of the difference in the effect of social transfers on output depicted by the model (i.e., 0.71) reflects the prevalence of HtM individuals, α, vis-à-vis the fiscal targeting effort aimed to reach HtM individuals beyond their population representation as depicted by the STT (recall that $STT \equiv \theta - \alpha$). Recall that while the share of HtM agents, α, is a structural parameter considered to be outside of the fiscal policy scope and more related to the degree of economic and financial development as well as economic policies in the financial sector, social transfer targeting, STT, is a key aspect of fiscal policy, especially determined by θ. Naturally, since in the benchmark parametrization only α and θ are allowed to vary, these two mechanisms jointly account, by design, for all the difference in the effect of social transfers on output depicted by the model. Also recall that, as discussed in Subsection 4.3, based on a large sample of countries, generally $\alpha \approx \theta$, which in turn implies that $STT \approx 0$. That is to say, when considering the universe of all types of social transfers, countries' ability to reach HtM individuals seems to mainly reflect the prevalence of HtM individuals, α, as opposed to a fiscal targeting effort aimed to reach HtM individuals beyond their population representation (i.e., there is very little social transfer targeting). This global regularity does not escape to our developed and Latin American samples where $\alpha_{Developed} = 0.23$, $\alpha_{Latin\ America} = 0.60$, $STT_{Developed} = 0.02$ and $STT_{Latin\ America} = 0.05$. While Latin American countries have a much larger share of HtM individuals, α, than developed countries, social transfers targeting, STT, is very similar across both samples of countries.[45] It

[44]The long-run multiplier is defined as the discounted sum of changes in output divided by the discounted sum of changes in social transfers.

[45]It is also worth noting that the standard deviation of STT within each sample of countries is relatively low: 2.9

should prove no surprise then that while the difference in the share of HtM individuals, α, explains 91 percent of the STM size difference between developed and Latin American countries, the share of social transfers reaching them, STT, explains 9 percent of such difference.[46] In other words, when considering all types of social transfers, Latin American countries depict large STMs mainly as a consequence of having, unfortunately, a large part of its population being HtM individuals as opposed to a particularly exceptional targeting of social transfers.[47]

Lastly, we now allow other parameter values (other than α and θ) to be calibrated for Latin American countries. In particular we follow De Mello and Moccero (2011) who find more accommodative Taylor rules in Latin America (in particular, $\phi_\pi = 1.19$, $\phi_Y = 0.01$, and $\phi_R = 0.61$). Other parameter values are selected as follows for Latin American countries: discount rate $\beta = 0.988$, sticky wage elasticity $\varepsilon_w = 10.50$ (matching 10% unemployment rate), steady-state government purchases $G_{ss} = 0.19$ (from World Development Indicators), and capital share $\mu = 0.35$ (in order to match K/Y from KLEMS). Since macroeconomic and inflation volatility is larger in emerging markets, the price-setting behavior in those countries is less rigid (see Barros et al., 2009, for Brazil). For this reason, we calibrate a higher frequency of price adjustments in developing countries (1.5 times a year relative to once a year in the developed world). This implies Calvo probabilities $\gamma_p = \gamma_w = 0.625$. Based on this alternative calibration exercise, the quantitative STM delivered by the model on impact is 0.84 in the Latin American sample, only 0.08 smaller than the benchmark calibration. Moreover, the prevalence of HtM individuals, α, and the fiscal targeting effort aimed to reach HtM individuals beyond their population representation, STT, help explains about 80 and 8 percent, respectively, of the overall difference in the effect of social transfers on output depicted by the model (i.e., 0.71). This implies that about 12 percent of the overall difference in the effect of social transfers on output depicted by the model (i.e., 0.71) is explained by other parameter differences between developed and Latin American countries.[48][49]

To sum up, a standard calibrated TANK model is able to match key STM empirical regularities shown in Section 2 in terms of the crucial role of the higher share of financially constrained individuals who live HtM in the Latin American sample relative to the developed countries has in explaining the large difference in the size of STMs previously estimated as well as regarding the main macroeconomic variables involved, and temporal profile for both the developed and Latin

percent and 2.2 percent in Latin American and developed countries, respectively. The same holds true when using the joint sample: 2.6 percent.

[46] Using the baseline calibration for developed economies, the counterfactual multiplier when the economy has $\alpha_{Latin\ America} = 0.60$ and $STT_{Latin\ America} = 0.05$ (i.e. $\theta_{Latin\ America} = 0.65$) is equal to $STM = 0.65$. Therefore, it explains 91 percent of the difference: (0.71 - 0.65)/0.71)*100 = 91. The remaining 9 percent difference in the STM is explained by the fact that $STT_{Latin\ America} = 0.05$.

[47] Appendix 4 shows on-impact STMs values using our benchmark calibration and combinations of α and θ which are allowed to vary between 0 and 1. This exercise provides additional insights as to the relative importance of α vis-à-vis θ driving large STMs.

[48] In particular, 6 percent is due to differences in monetary policy, 4 percent given by heterogeneity in nominal rigidities and 2 percent of the difference by other factors.

[49] Table A.6.1. in appendix 6, shows on Impact STMs against additional scenarios

American samples.

7 Final thoughts

Based on novel empirical evidence and quantitative results, we have shown the critical implications of having large shares of financially constrained individuals on the size of the STM. A larger share of individuals living hand-to-mouth causes social transfer shocks to easily reach individuals with a high marginal propensity to consume which, in turn, increases aggregate consumption and output. For this reason, the effect on output is mainly driven by consumption while investment remains mostly unchanged. These findings coupled with the evidence supporting a larger share of HtM agents in emerging markets (beyond that of our six Latin American countries) suggest that a larger STM may be expected for emerging market economies in general.

Two further reflections emerge from our analysis, especially when translating our findings into fiscal policy action. First, given the large size that the STM can achieve especially in emerging markets, social transfers emerge as a natural fiscal policy tool to help vulnerable families who are financially constrained and at the same time help the economy to recover faster. In this sense, social transfers seem to provide an inclusive manner to deal with temporary and deep recessions, like during the COVID-19 pandemic. Second, because most of the effect of a social transfer shock impacts the economy especially in the short- and medium-run (as opposed to having truly long-lasting effects) and through private consumption (as opposed to via increasing the economy's productive capacity and investment), this type of fiscal policy tool is far from ideal to increase long-term growth and productivity.

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Appendices

Appendix 1. Data definitions and sources

All series are quarterly and seasonally adjusted. If they are not seasonally adjusted from the original source, we apply a seasonal adjustment following the U.S. Census Bureau's X-13ARIMA-SEATSX-13. All series are expressed in millions of national currency, in constant prices, deflated using the implicit GDP deflator derived from quarterly national accounts for each country.[50]

GDP, private consumption, private investment (gross fixed capital formation to be precise), and GDP deflator sources: Argentina (Dirección Nacional de Cuentas Nacionales, INDEC), Brazil (Instituto Brasileiro de Geografia e Estatística, IBGE), Chile (Banco Central de Chile), Colombia (Departamento Administrativo Nacional de Estadística, DANE), Mexico (Instituto Nacional de Estadística, Geografía e Informática, INEGI), Peru (Instituto Nacional de Estadística e Informática, INEI, Banco Central de Reserva del Perú, BCRP), United States (Economic Research Division, Federal Reserve Bank of St. Louis), and European countries (Eurostat [Last update: 16.09.19. Extracted on: 17.09.19]).

Social transfers sources: Argentina (Dirección Nacional de Política Fiscal y de Ingresos. Subsecretaría de Programación Macroeconómica. Secretaría de Política Económica, Ministerio de Hacienda), Brazil (STN, IBGE, IPEA e BCB), Chile (Dirección de Presupuestos (DIPRES) / Banco Central de Chile), Colombia (Ministerio de Hacienda y Crédito Público), Mexico (Dirección General de Estadística de la Hacienda Pública. Unidad de Planeación Económica de la Hacienda Pública.), Peru (Government Finance Statistics (GFS) - IMF), United States (Economic Research Division, Federal Reserve Bank of St. Louis), and European countries (Eurostat [Last update: 19.07.19. Extracted on: 17.09.19]).[51]

Total government spending and revenues: Argentina (Ministerio de Economía en base a datos de la Secretaría de Hacienda), Brazil (STN, IBGE, IPEA e BCB), Chile (Dirección de Presupuestos (DIPRES) / Banco Central de Chile), Colombia (Dirección General de Política Macroeconómica, Ministerio de Hacienda y Crédito Público), Mexico (Dirección General de Estadística de la Hacienda Pública. Unidad de Planeación Económica de la Hacienda Pública.), Peru (Ministerio de Economía y Finanzas, Banco de la Nación), United States (Economic Research Division, Federal Reserve Bank of St. Louis), and European countries (Eurostat [Last update: 19.07.19. Extracted on: 17.09.19]).

Central bank interest rates: Global Financial Data and central banks' websites.

Sample period to the estimation of social transfer multipliers: Argentina (2004Q1-2019Q4), Austria (2001Q1-2019Q1), Belgium (1995Q1-2019Q1), Brazil (2010Q1-2019Q4), Chile (2005Q1-2019Q4), Colombia (2000Q1-2018Q4), Denmark (1999Q1-2019Q1), Finland (1999Q1-2019Q1), France (1980Q1-2019Q1), Germany (2002Q1-2019Q1), Greece (1999Q1-2019Q1), Ireland (2002Q1-2019Q1), Italy (1999Q1-2019Q1), Luxembourg (2015Q1-2019Q1), Mexico (2007Q1-2019Q1), Netherlands (1999Q1-2019Q1), Norway (2002Q1-2019Q1), Peru (1995Q1-2018Q4), Portugal (1999Q1-2019Q1), Spain (1995Q1-2019Q1), Sweden (1995Q1-2019Q1), United Kingdom (1987Q1-2019Q1), and United States (1960Q1-2019Q4).

[50] IMF (2017). Quarterly National Accounts Manual. Statistics Department, International Monetary Fund, 2017 Edition, Washington, D.C.

[51] Since the series on unemployment insurance spending are not available at quarterly frequency, we proceed to interpolate it based on annual frequency data for each country. As a robustness check for this approach, and assuming that short-term fluctuations in unemployment insurance spending are mainly driven by changes in the number of unemployed workers, we use such information on unemployment (which is available at quarterly frequency) to guide the weights used in the interpolation procedure. This alternative approach leaves our findings virtually unchanged.

Appendix 2. Basic facts of HtM and non-HtM individuals

On top of questions FIN24, FIN37, and FIN38 (already discussed in the main text, sub-section 4.1), in this Appendix, we also used the following questions from Global Findex Data to help characterize basic relevant facts of HtM and non-HtM individuals:

- Question FIN25 (which is included in the financial resilience section) asks the surveyed individual in case of responding positive to FIN24 "What would be the main source of money that you would use to come up with [1/20 of GNI per capita in local currency] within the next month?" The possible answers being one of the following: "savings", "family, relatives, or friends" or "money from working", "borrowing from a bank, employer, or private lender", "selling assets", or "some other source". We use this question to show that while savings is the most important (yet hardly the single) mechanism to cope with a financial shock in the developed world, it is more limited in emerging markets where "family, relatives, or friends" seem to be more relevant. We also show that selling assets is not very relevant either in developed or emerging markets supporting that illiquid wealth does not seem to be very relevant in dealing with a financial shock.
- Question FIN19 (which is included in the borrowing section) asks the surveyed individual "[d]o you, by yourself or together with someone else, currently have a loan you took out from a bank or another type of formal financial institution to purchase a home, apartment, or land?", respectively. The possible answers being "yes" or "no". We use this question to provide an insight regarding the so-called wealthy HtM individuals identified in previous studies for developed countries. In particular, we distinguish HtM individuals into those having a property loan (as a proxy of a particular type of relevant wealthy HtM individual) and those not having a property loan (as a proxy of the so-called poor HtM).
- Individual characteristic variables regarding income, educational attainment, age, sex, and labor status, in particular depending on whether the individual is part of the workforce and his/her employment status.

2.1. How relevant are individual savings to deal with a financial shock?

Figure A.2.1 shows the main source of funds non-HtM individuals report would use to deal with a financial shock. In line with the literature available for developed countries which relies on liquid wealth (as opposed to total wealth which also includes illiquid assets, e.g. houses), individuals from this set of countries would mainly rely on savings (see blue bars in Panel A) and very little on selling assets (see blue bars in Panel E). In fact, the main reliance of non-HtM individuals on savings as a source to cope with a financial shock in developed economies is of 59.3 percent, distantly followed by funds originating from family, relatives, or friends (with an average of 16 percent) and money from working (with an average of 12.9 percent). On the other hand, selling assets as a main source of funding is supported only by 1.4 percent of non-HtM individuals.

FIGURE A.2.1

Notably, while still important, savings are much less relevant in emerging markets. In fact, the funds originating from family, relatives, or friends are, on average, 36.6 percent (i.e., more than twice of that depicted in developed countries), followed by savings and money from work (representing 28.3 and 24.2 percent, respectively). It is also worth noting that, in emerging markets, the share of non-HtM individuals asserting to the selling of assets to deal with a financial shock is also very low and virtually identical to that observed in the developed economies. On average, only 1.5 percent of non-HtM individuals in emerging markets would rely on selling assets which, in turn, also support that liquid wealth seems to be more relevant in dealing with a financial shock in this part of the world.

2.2. Wealthy HtM individuals: Does this kind also exist in emerging markets?

We now explore the relevance of wealthy HtM arguments outside the developed world. Unfortunately, we do not have rich portfolio data. However, we can identify whether HtM individuals have a real estate property loan or not. While not ideal, this is very relevant information because, as discussed in great detail in Kaplan et al. (2014), housing wealth is an important source of wealth behind wealthy HtM and because between 50 and 70 percent of owner-occupied homes have a mortgage in developed countries.[52] For example, Kaplan et al. (2014) find that HtM households due to "only house wealth" is about 6 percent of all households in the United States and 2 percent in Germany.

Panels A and B in Figure A.2.2 split the share of HtM individuals reported in Figure 4, into those who have a standing property loan and those who do not. Making a stretch in the use of the words, we refer to the share of wealthy HtM (α_W) and poor HtM (α_P). Panel A shows that, like in the developed world, wealthy HtM individuals are also present in emerging markets. On average, the share of wealthy HtM is 4.1 and 3.6 in developed and emerging markets, respectively.[53] Interestingly, yet not surprising, Panel B in Figure A.2.2 shows that while wealthy HtM constitute a relevant share of the population in developed countries, it is less so in emerging markets where the HtM phenomenon is largely driven by poor HtM individuals. On average, the share of poor HtM is 17.1 and 39.1 in developed and emerging markets, respectively.

FIGURE A.2.2

2.3. Main characteristics of HtM individuals

We now analyze whether the capacity to deal with a financial shock varies across several plausible relevant economic and demographic individual and household characteristics available in Global Findex. Table A.2.1 shows the share of HtM individuals by household income quintile, education level, age, sex, and labor status, in particular depending on whether the individual is part of the workforce and his/her employment status. Table A.2.2 reports marginal effects from probit regressions in which the dependent variable equals 1 if the individual is HtM and 0 if he/she is not HtM; both one-characteristic-at-a-time and all of them jointly. Both tables report these relevant data for all countries as well as for emerging and developed countries separately.

TABLE A.2.1 AND TABLE A.2.2

The findings support that individuals with higher household income, greater educational attainment, male, and employed report a higher capacity to deal with a financial shock, both in developed and emerging countries (with even similar R^2 values among these groups). The main discrepancy

[52] See, for example, https://fivethirtyeight.com/features/how-many-homeowners-have-paid-off-their-mortgages/ and https://www.statista.com/statistics/957803/homeowners-with-and-without-an-outstanding-mortgage-in-eu-28-per-country/#:~:text=An%20average%2026.5%20percent%20of,like%20the%20Netherlands%20and%20Sweden..

[53] It is worth noting that our findings based on a not ideal measure are quite similar to those relying on more sophisticated analysis for industrial countries like in Kaplan et al. (2014). For example, Panel A reports that in Figure A.3.2 the share of HtM individuals with property loan is 4.6 percent in the United States and 1.5 percent in Germany.

between developed and emerging countries is related to the relevance of age. While in emerging markets the older the individual, the lower their capacity to deal with a financial shock, in developed countries, respondents aged 15 to 34 report themselves as being more financially vulnerable. All in all, the relevance of this set of economic and demographic characteristics as well as their ability to predict HtM individuals is comparable to previous studies. These findings are broadly consistent with those of other studies focusing on the developed world (e.g., Lusardi et al., 2011). Moreover, if one also included all possible interactions among these economic and demographic characteristics, the R^2 would reach about one-third (regression results are not shown for the sake of brevity).

Appendix 3. Country share of HtM individuals, share of social transfers reaching HtM individuals, and social transfers targeting

Table A.3.1 shows the country share of HtM individuals, share of social transfers reaching HtM individuals, and social transfers targeting from Global Findex dataset (based on its latest survey for the year 2017).

TABLE A.3.1

Appendix 4. Additional insigths regarding the relative importance of α vis-à-vis θ driving large STMs

Table A.4.1 shows on-impact STM values using our benchmark calibration and combinations of α and θ which are allowed to vary between 0 and 1 in 0.05 intervals. The shaded cells indicate combinations of α and θ such that $STT < 0$. Recall that since $STT \equiv \theta - \alpha$, then $STT < 0$ implies that $\alpha > \theta$.

TABLE A.4.1

This exercise provides additional insights as to the relative importance of α vis-a-vis θ driving large STMs. In particular, the results show that it is not feasible to obtain truly large on-impact STMs (e.g., $STM > 1$) for low to moderate values of the share of HtM individuals, α, (e.g., $\alpha < 0.4$). This implies that, in spite of important social transfers targeting efforts, even if θ was the maximum possible (i.e., $\theta = 1$), in order to be able to achieve truly large on-impact STM, there exists the need to have large propagation forces via high average marginal propensity to consume, which can only be achieved by having a relatively large share of HtM individuals, α. In the extreme, for a sufficiently high share of HtM individuals, α, (e.g., $\alpha > 0.8$) it is possible to have truly large STMs even when θ is low enough such that $STT < 0$. This quantitative importance of the share of HtM individuals, α, provides another relevant dimension as to how to rationalize its practical importance in determining the size of STM in Latin America as well as in other emerging market economies with high prevalence of HtM individuals.

Appendix 5. Sensitivity Analysis on Basic Specification

Tables A.5.1 and A.5.2 show on-impact STM values after taking 1, 2 and 3 percent off the distribution of social transfers and taking out one country at a time respectively.

TABLE A.5.1

TABLE A.5.2

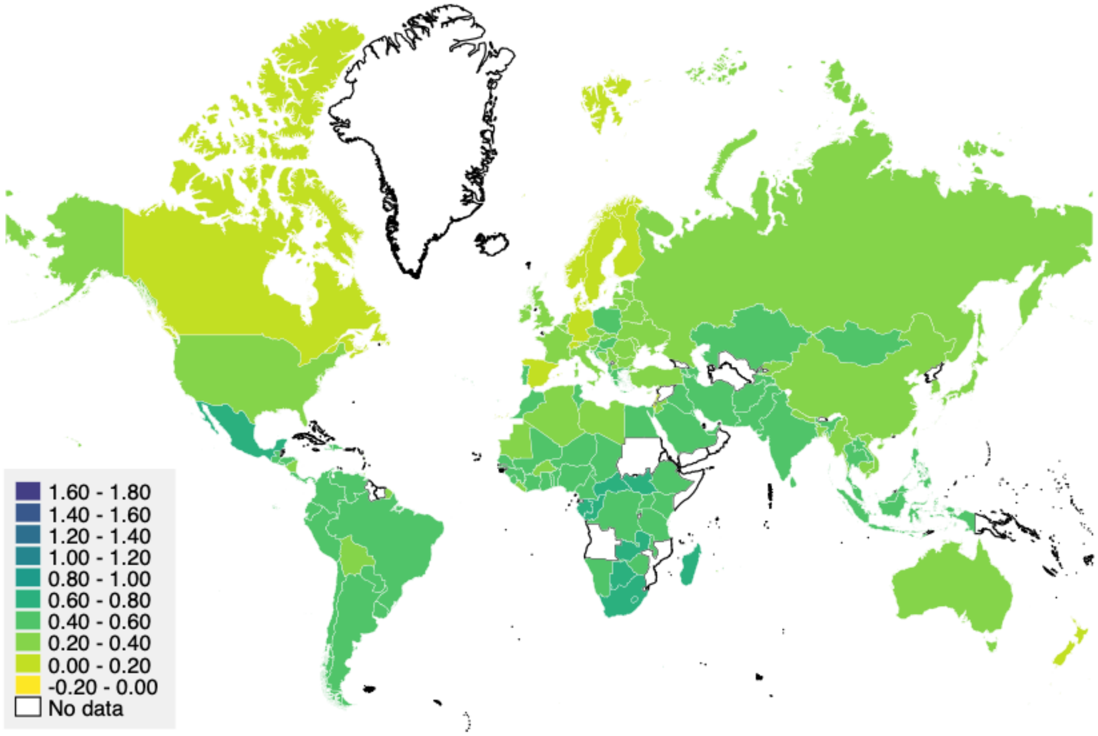
Appendix 6. On-Impact STMs under different Targeting and Monetary Assumptions

Table A.6.1 in the appendix (represented below) to show the county specific STM, with different assumptions about the persistent of the social transfer shock (baseline persistence vs one-time shock) and more accommodative monetary policy (baseline vs ZLB binding for 5 years).

TABLE A.6.1

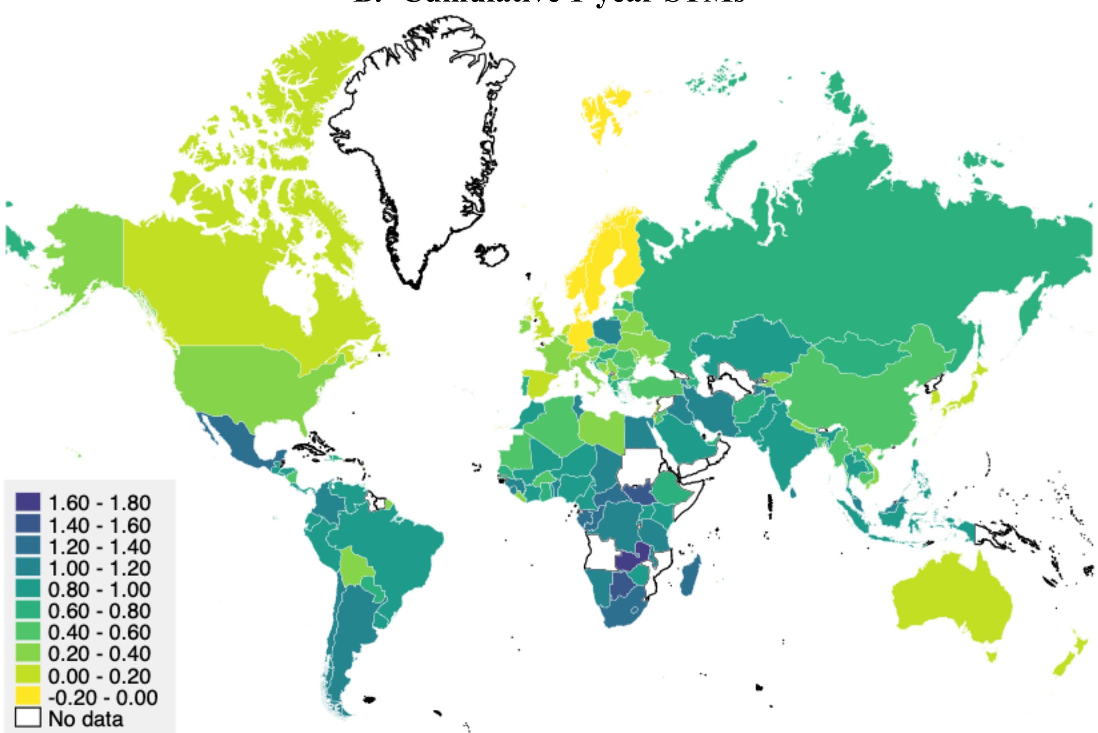
Map 1. Projected STMs based on share of HTM

A. On impact STMs



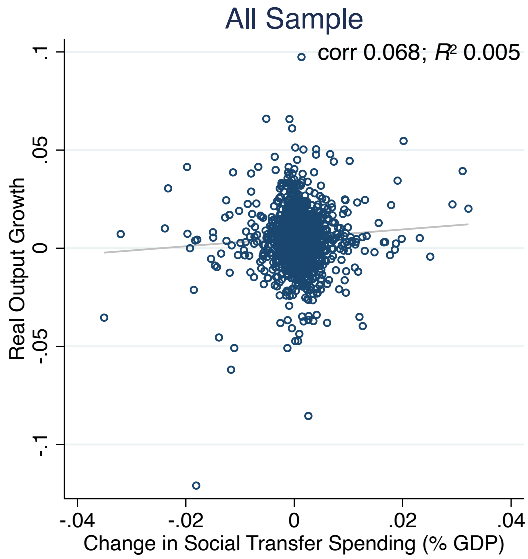
Source: Author Calculations

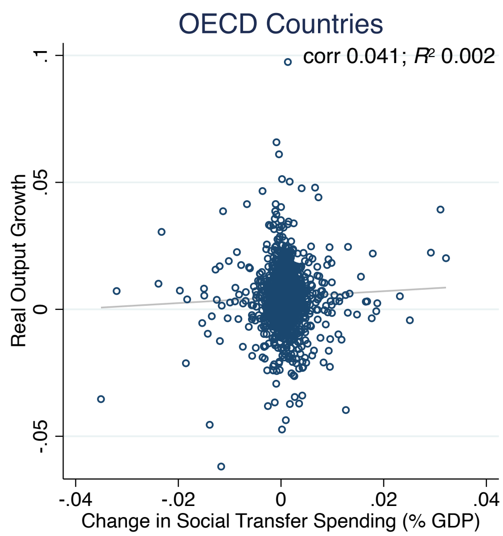
B. Cumulative 1-year STMs



Source: Author Calculations

Figure 1. Basic Scatter Plots Transfer Spending vs. Output Growth





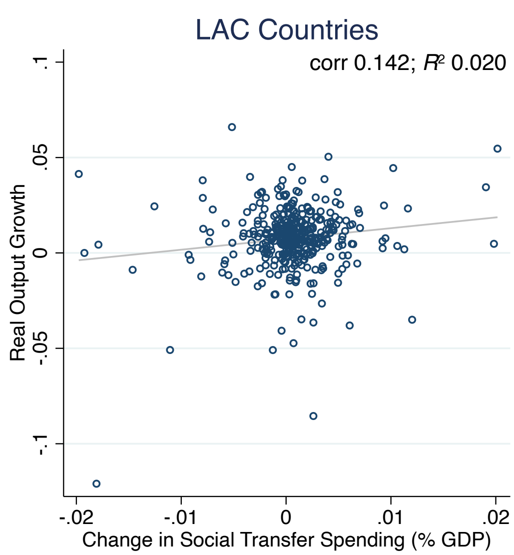


Figure 2. Social transfer multipliers:

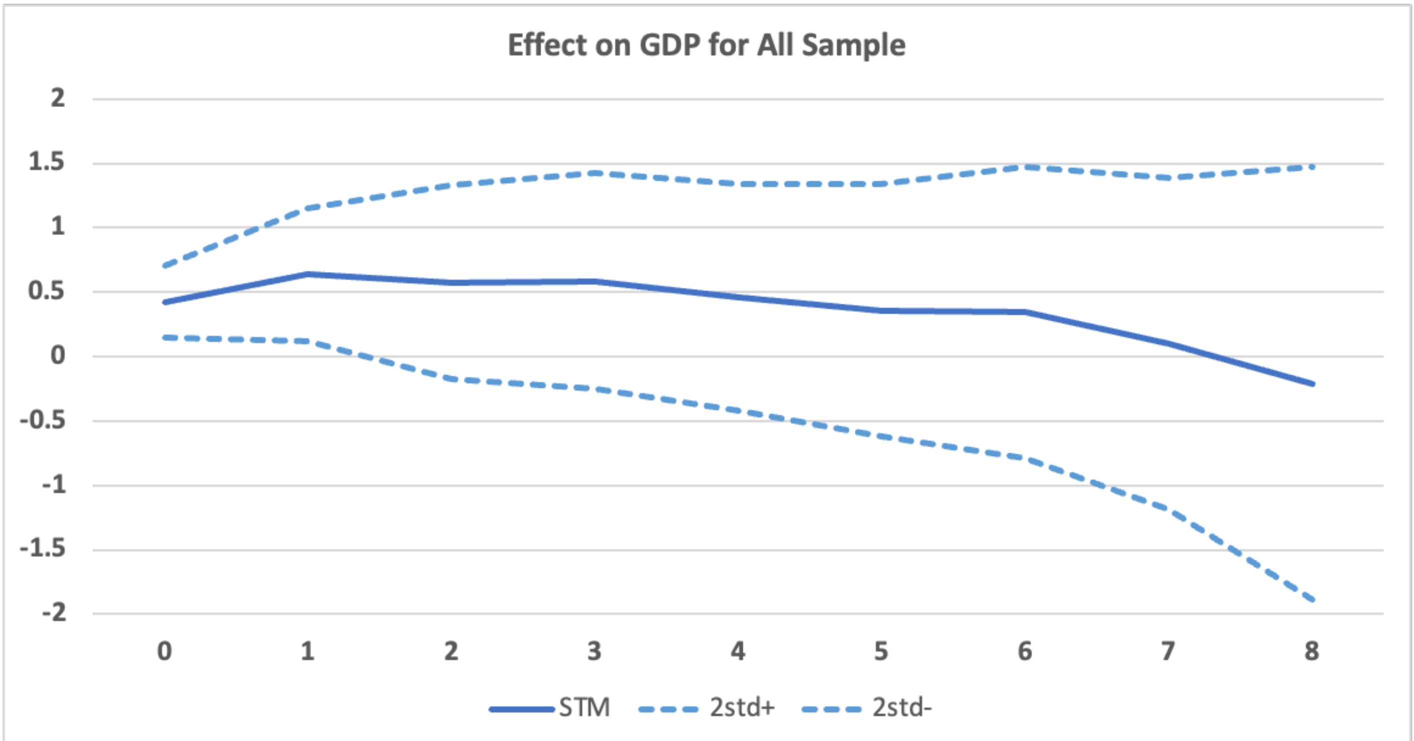
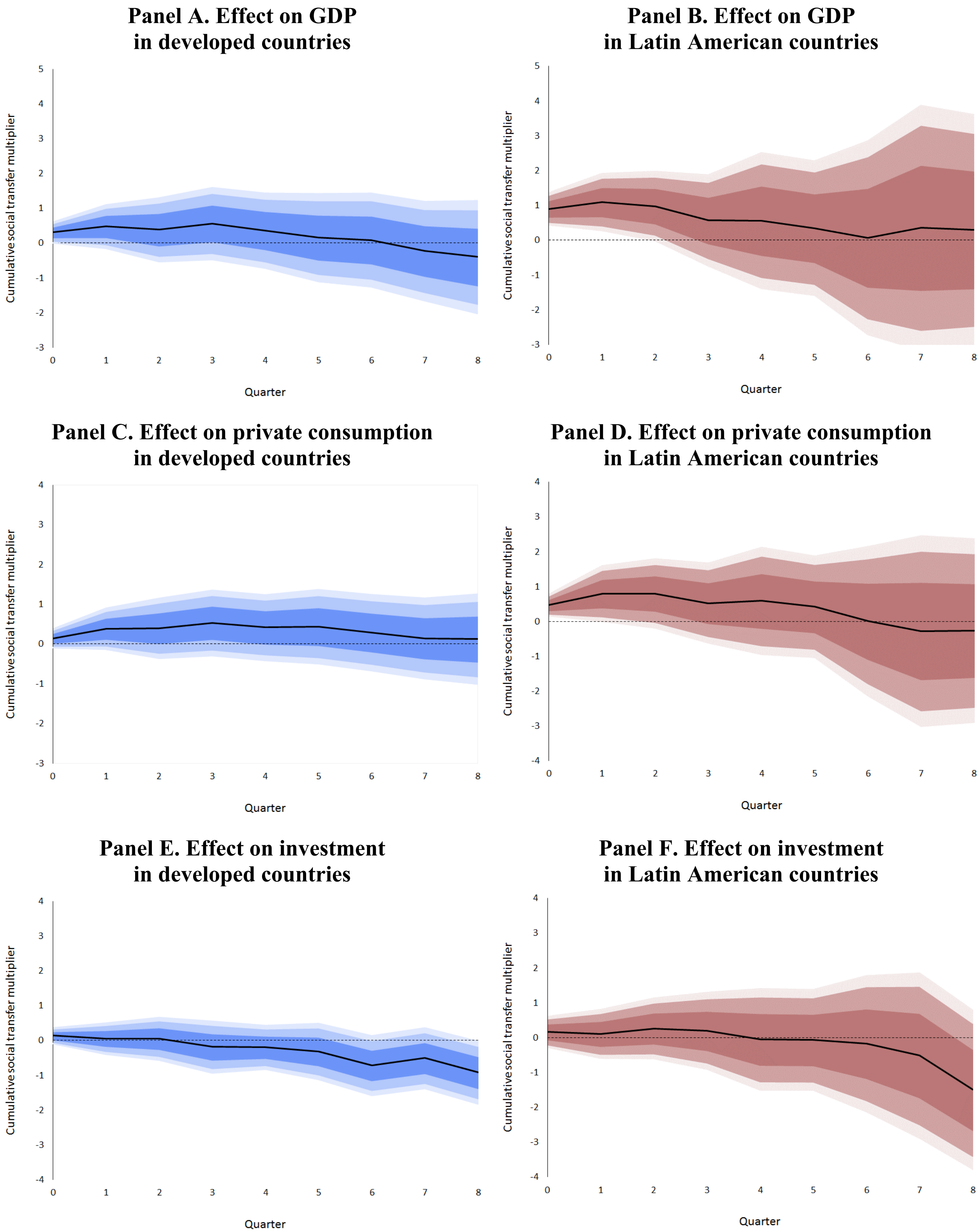
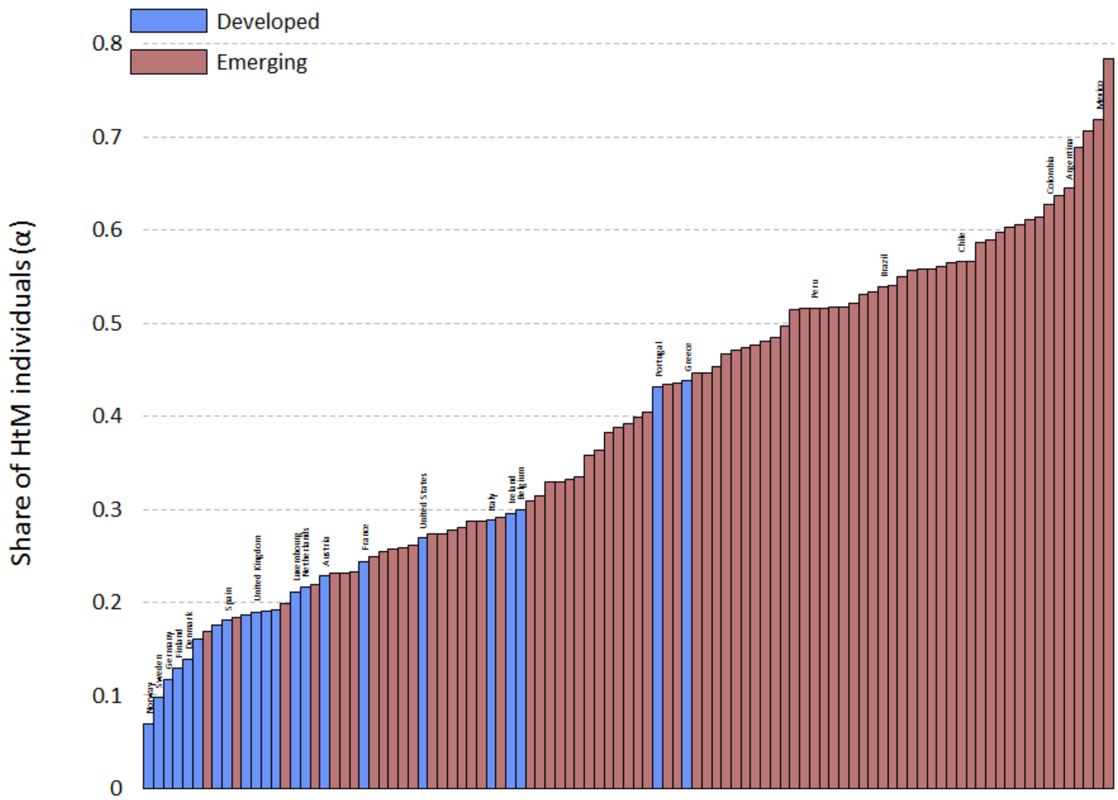


Figure 3. Social transfer multipliers:
Empirical estimation for Latin American and developed countries



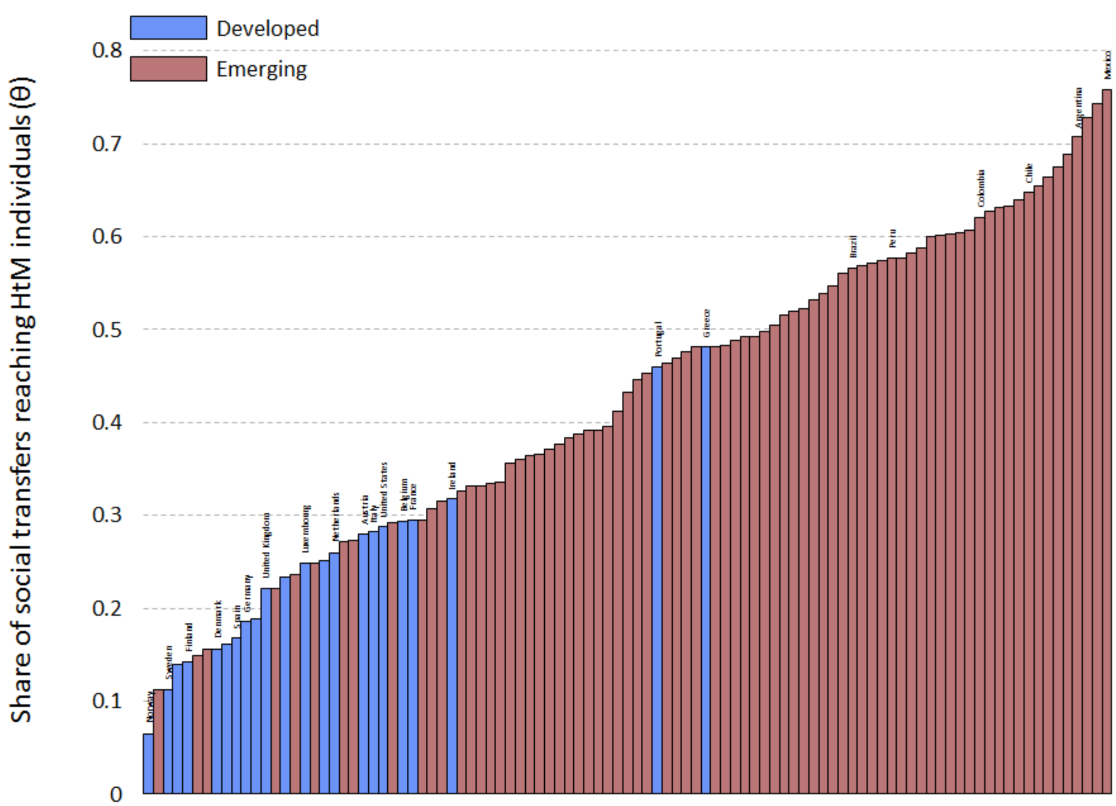
Notes: The STM measures the effect of a $1 change in social transfers on the level of GDP (Panels A and B), consumption (Panels C and D), and investment (Panels E and F). Dark, medium, and light areas show standard errors at 68, 90, and 95 percent confidence intervals, respectively.

Figure 4. Country share of hand-to-mouth individuals



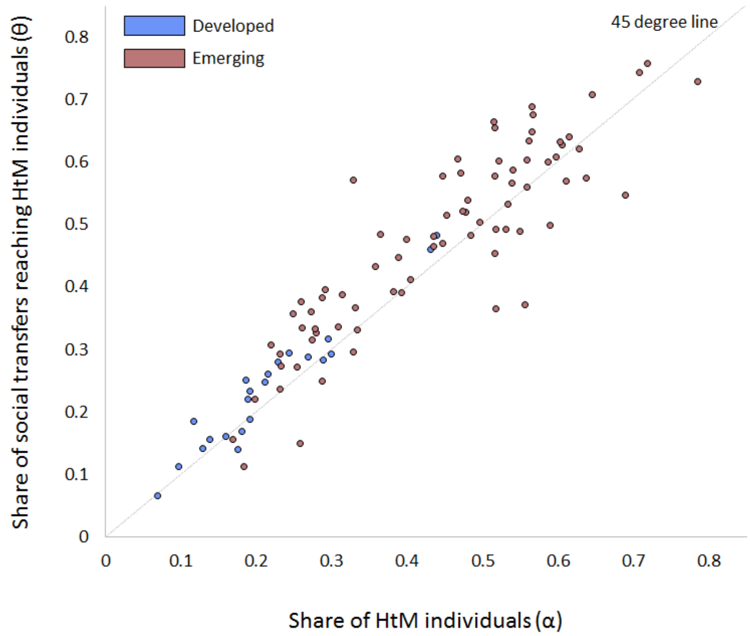
Notes: Authors' calculation based on Global Findex database.

Figure 5. Country share of social transfers reaching hand-to-mouth individuals



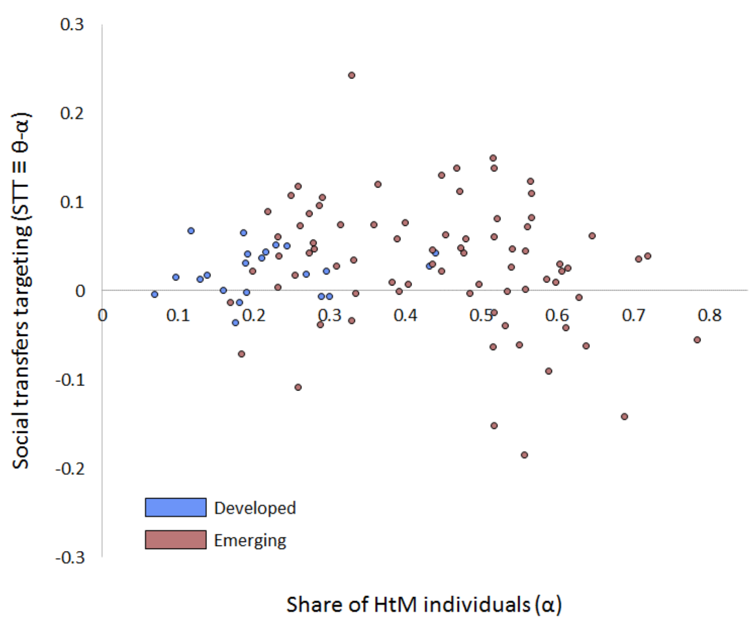
Notes: Authors' calculation based on Global Findex database.

Figure 6. Country share of social transfers reaching hand-to-mouth individuals vs. share of hand-to-mouth individuals



Notes: Authors' calculation based on Global Findex database.

Figure 7. Country social transfers targeting vs. share of hand-to-mouth individuals



Notes: Authors' calculation based on Global Findex database.

Figure 8. Social transfer multipliers by Share of HtM

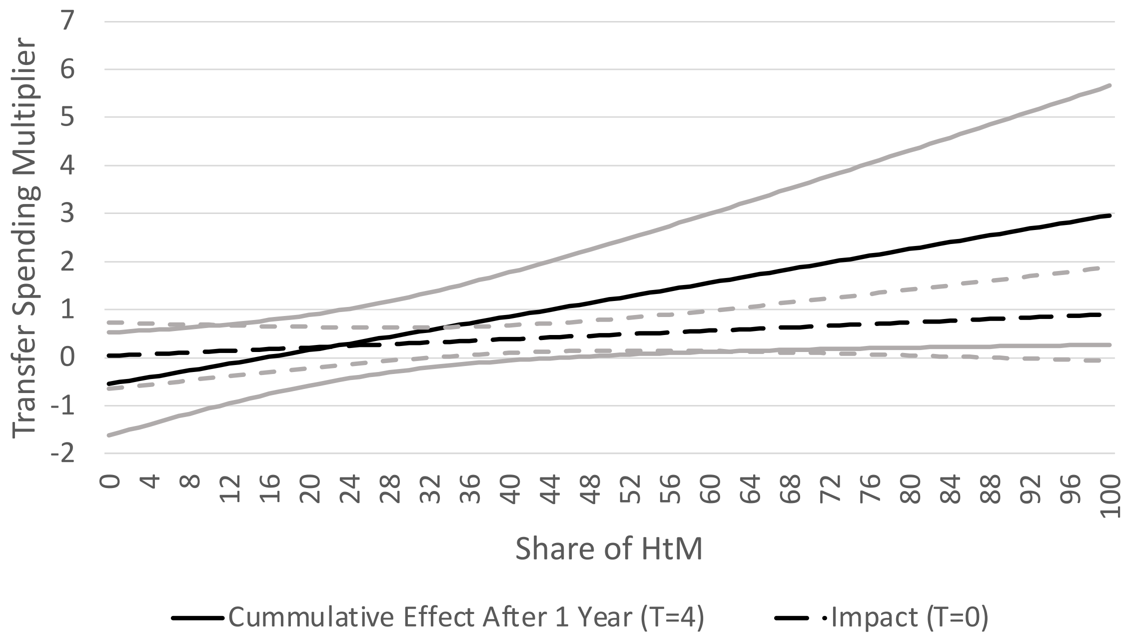
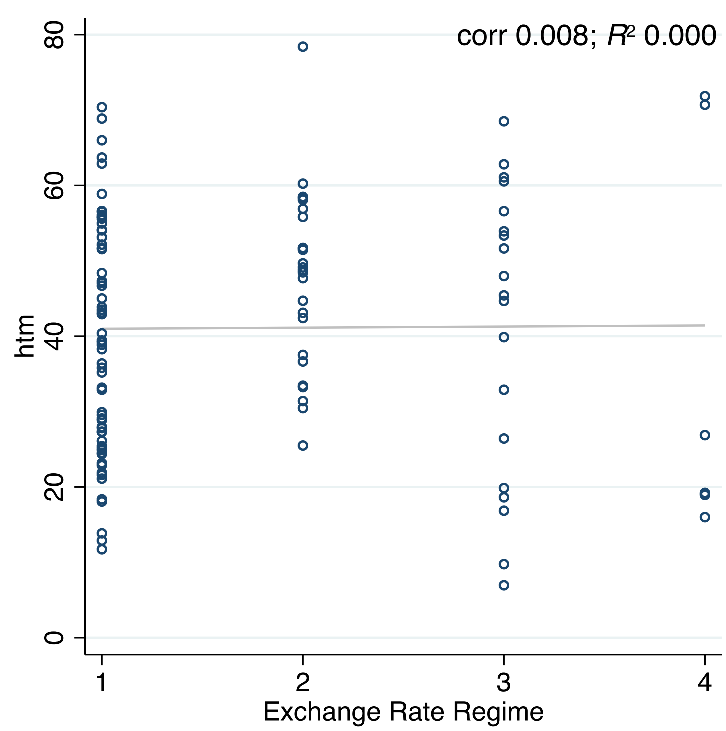


Figure 9. HtM Correlations with Other Potential STM Drivers
Panel A: Trade Openness

Notes: utilizes data from a global sample of 113 countries based on data availability

Panel B: Exchange Rate Regimes



Notes: utilizes data from a global sample of 112 countries based on data availability
:

Figure 10. A. Individual (country) On Impact STMs Against Model Implied Slope

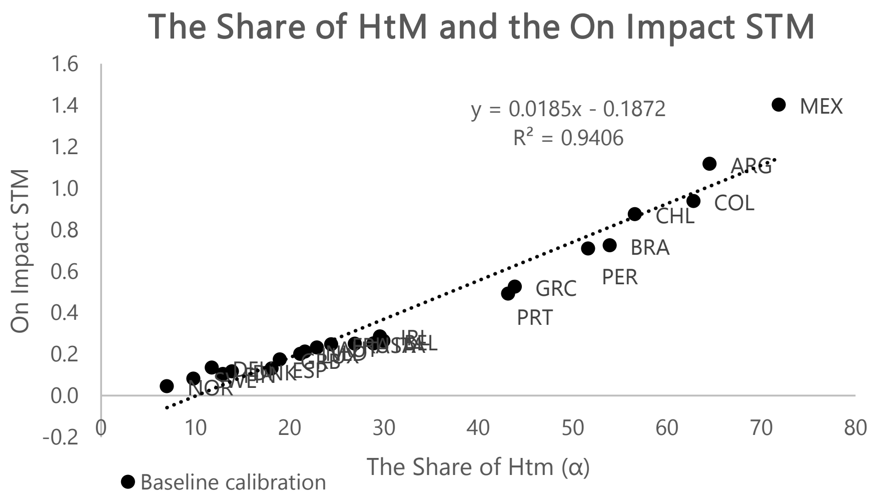
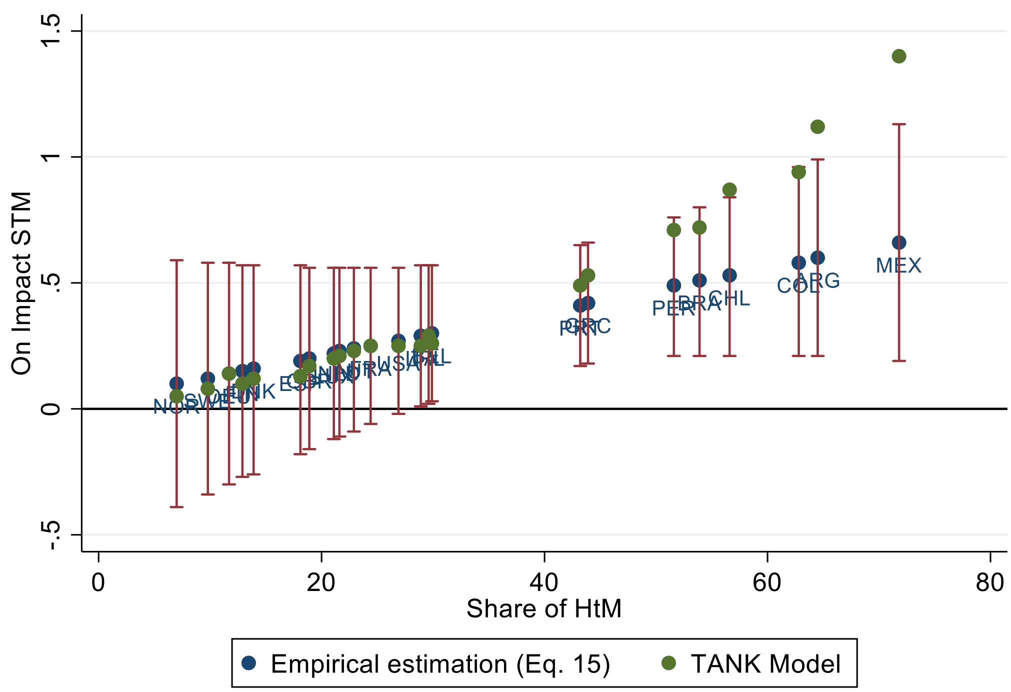


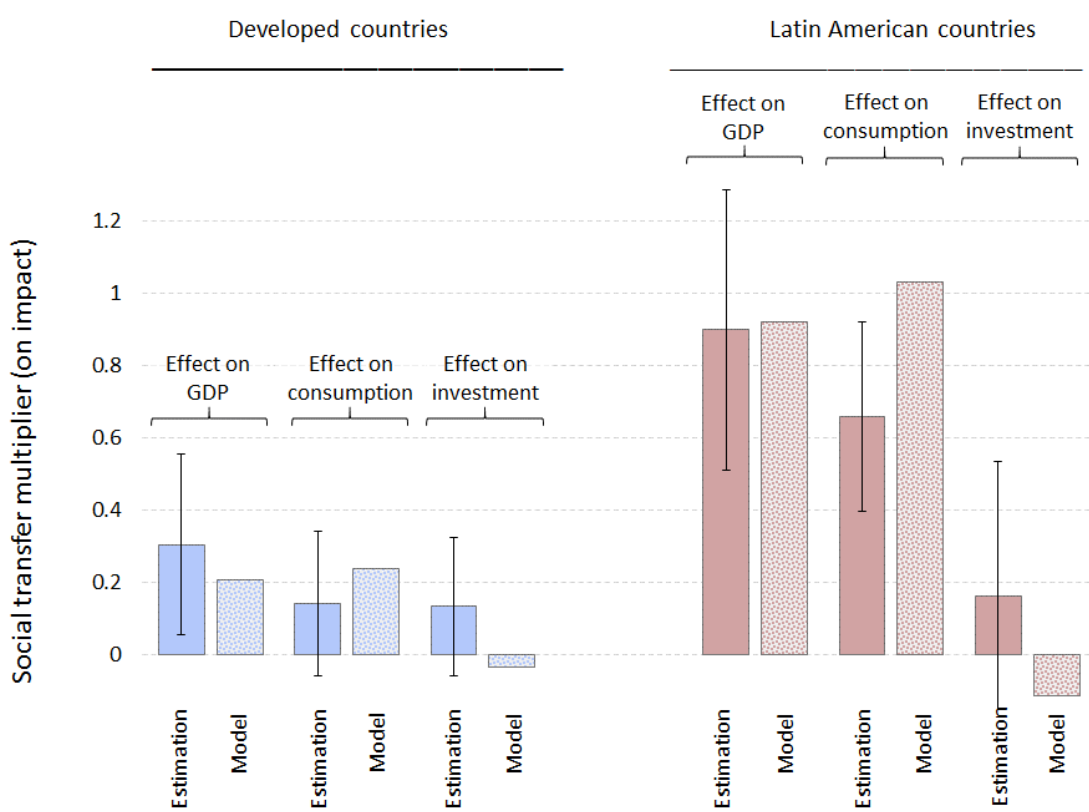
Figure 10. B. Individual (country) On Impact STMs comparison: Empirical estimation versus model



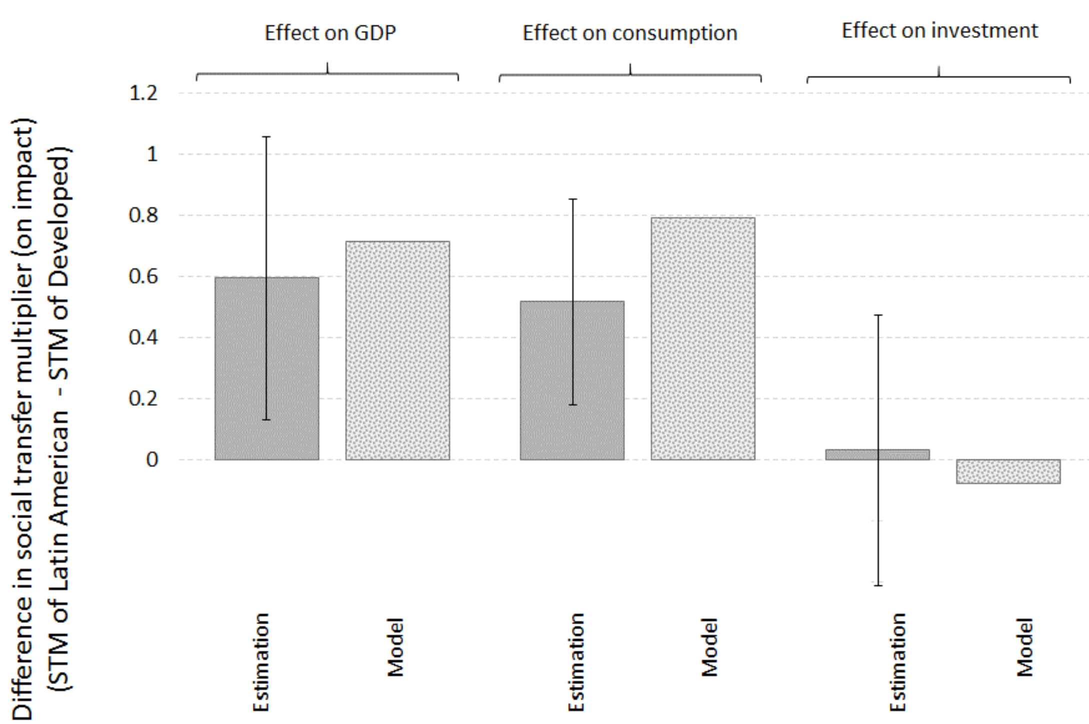
Note: Confidence intervals at 90 percent.

Figure 11. Social transfer multipliers:
Empirical estimation versus model quantitative results

Panel A. Size of social transfer multipliers



Panel B. Difference in size of social transfer multipliers



Notes: Standard errors depict 90 percent statistical significance error bands.

Figure 12. Social transfer multipliers: Model quantitative results

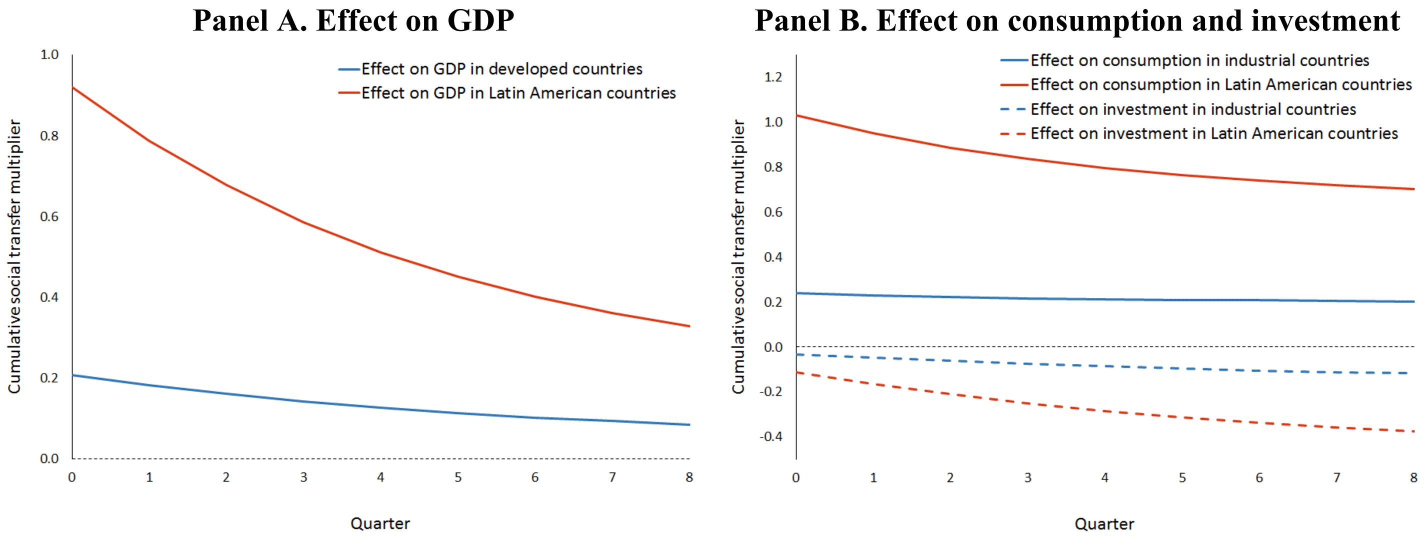


Table 1. Summary Statistics

VARIABLES	N	Mean	Stdev	Median	p5	p95
Real GDP Growth	2,026	0.5	1.3	0.6	-1.4	2.3
Social Spending (% GDP)	2,026	12	5.1	14	3.0	19
Change in Social Spending (% GDP)	2,026	0.07	0.4	0.06	-0.3	0.5
Social Spending Net of Automatic Stabilizers (% GDP)	1,804	11	4.7	12	2.9	18
Change in Social Spending Net of Automatic Stabilizers (% GDP)	1,795	0.07	0.4	0.06	-0.3	0.5
Government Expenditure (% GDP)	1,960	41	12	44	17	56
Change in Government Expenditure (% GDP)	1,958	0.2	2.3	0.2	-1.6	2.1
Real Government Revenues (% GDP)	1,992	39	12	41	18	55
Change in Real Government Revenues (% GDP)	1,990	0.2	2.2	0.2	-1.7	2.0
Real Private Consumption (% GDP)	1,944	57	8.7	58	44	69
Change in Real Private Consumption (% GDP)	1,942	0.3	0.8	0.3	-0.7	1.3
Real Gross Fixed Capital Formation (% GDP)	1,944	21	3.4	22	16	26
Change in Real Gross Fixed Capital Formation (% GDP)	1,942	0.1	2.0	0.1	-1.1	1.4
Inflation	1,994	1.3	17	0.6	-0.5	2.5
Central Bank Interest rate	2,011	8.1	143	2.5	-0.4	15

Table 2. On Impact STM Multiplier Under Different Specifications

VARIABLES	Real GDP Growth LSDV	Real GDP Growth LSDV	Real GDP Growth BP	Real GDP Growth BP IV	Real GDP Growth GMM_IV
Change in Social Spending (% GDP)	0.301***			0.366**	
	(0.0915)			(0.147)	
Change in CA Social Spending net of AS (% GDP)		0.299***			0.272**
		(0.106)			(0.108)
Change in Unanticipated CA Social Spending net of AS (% GDP)			0.389**		
			(0.149)		
Observations	1,802	1,637	1,602	1,602	1,674
Adjusted R-squared	0.219	0.214	0.215	0.349	
Number of countries	23	23	23	23	23
Fixed Effects	YES	YES	YES	YES	YES
Time Effects	YES	YES	YES	YES	
Controls	YES	YES	YES	YES	YES
Underidentification - Weak Identification - Weak Instruments Tests					
LM test statistic for underidentification				80.92	
p-value of underidentification LM statistic (Anderson or Kleibergen-Paap)				0.000	
F statistic for weak identification (Cragg-Donald or Kleibergen-Paap)				1269	
Anderson-Rubin chi-squared test of significance of endogenous regressors				6.078	
p-value of Anderson-Rubin chi-squared test of endogenous regressors				0.0137	
Sargan statistic					1679
p value of Sargan statistic					0.293
Hansen J statistic					20.96
p value of Hansen statistic					1.000

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. "CA" refers to Cyclically Adjusted and "AS" to Automatic Stabilizers. **Under-identification test**: Ho: matrix of reduced form coefficients has rank=K1-1 -under-identified. Ha: matrix has rank=K1-identified. **Weak identification test**: Ho: equation is weakly identified. Weak-instrument-robust inference. **Tests of joint significance of endogenous regressors B1 in main equation:** Ho: B1=0 and overidentifying restrictions are valid

Table 3. Correlations between HtM shares, Trade Openness, and Exchange Rate Regimes

OLS	(1)	(2)	(3)	Pearson-Correlation	-4	-5
VARIABLES	**HtM**	**HtM**	**HtM**	VARIABLES	**htm**	**htm**
Forex Regime	0.145		-0.304	**Forex Regime**	0.0085	
(SE)	(1.985)		(2.096)	**(P-Value)**	(0.929)	
Trade Openness		-0.0384	-0.0407	**Trade Openness**		-0.081
(SE)		(0.0391)	(0.0406)	**(P-Value)**		(0.396)
Constant	40.85***	43.64***	44.33***			
(SE)	(3.435)	(3.011)	(4.953)			
Observations	113	112	112		113	112
R-squared	0.000	0.007	0.007			

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Figure A.2.1. Country share of HtM individuals (α), share of social transfers reaching HtM individuals (θ), and social transfers targeting (STT)

Country	α	θ	STT	Our Sample
Albania	47.1	58.2	11.2	0
Algeria	33.4	33.2	-0.2	0
Argentina	64.5	70.7	6.2	1
Armenia	56.6	67.5	10.9	0
Australia	19.2	23.3	4.1	0
Austria	22.9	28.0	5.1	1
Azerbaijan	43.5	46.4	3.0	0
Bahrain	43.5	48.1	4.6	0
Belarus	30.9	33.6	2.8	0
Belgium	29.9	29.3	-0.6	1
Bolivia	29.1	39.6	10.5	0
Bosnia and Herzegovina	26.1	33.4	7.3	0
Botswana	78.4	72.9	-5.5	0
Brazil	53.9	56.6	2.7	1
Bulgaria	32.9	57.1	24.2	0
Canada	16.0	16.1	0.1	0
Chile	56.6	64.8	8.2	1
China	38.9	44.7	5.8	0
Colombia	62.8	62.1	-0.7	1
Costa Rica	54.0	58.7	4.7	0
Croatia	47.3	52.2	4.9	0
Cyprus	35.8	43.2	7.4	0
Czech Republic	36.4	48.4	12.0	0
Denmark	13.9	15.6	1.8	1
Dominican Republic	47.7	51.9	4.2	0
Ecuador	56.1	63.3	7.2	0
Egypt, Arab Rep.	59.7	60.7	1.0	0
El Salvador	55.6	37.1	-18.5	0
Estonia	27.3	31.6	4.2	0
Finland	12.9	14.2	1.3	1
France	24.4	29.4	5.0	1
Gabon	68.9	54.7	-14.2	0
Georgia	52.1	60.2	8.1	0
Germany	11.7	18.5	6.8	1
Greece	43.9	48.2	4.3	1
Guatemala	55.8	56.0	0.2	0
Hong Kong SAR, China	25.9	37.7	11.8	0
Hungary	44.7	46.9	2.2	0
India	53.4	53.3	-0.1	0
Indonesia	51.7	49.3	-2.4	0
Iran, Islamic Rep.	61.4	64.0	2.6	0
Iraq	58.9	49.8	-9.1	0
Ireland	29.6	31.7	2.2	1
Israel	16.9	15.6	-1.3	0
Italy	28.9	28.3	-0.6	1
Japan	19.1	18.9	-0.2	0
Jordan	33.2	36.6	3.5	0
Kazakhstan	49.7	50.4	0.8	0
Korea, Rep.	19.9	22.1	2.3	0
Kosovo	23.2	29.2	6.1	0
Kuwait	55.0	48.9	-6.1	0
Latvia	40.4	41.1	0.8	0
Lebanon	18.4	11.3	-7.1	0
Libya	28.7	24.9	-3.8	0
Lithuania	28.0	32.6	4.7	0
Luxembourg	21.1	24.8	3.7	1
Macedonia, FYR	25.4	27.2	1.8	0
Malaysia	61.1	56.9	-4.2	0
Malta	23.2	23.6	0.4	0
Mauritius	56.5	68.8	12.3	0
Mexico	71.8	75.8	4.0	1
Mongolia	45.3	51.5	6.3	0
Montenegro	21.9	30.8	8.9	0
Morocco	51.7	36.5	-15.2	0
Namibia	63.7	57.5	-6.2	0
Netherlands	21.6	26.0	4.4	1
New Zealand	18.6	25.1	6.5	0
Norway	7.0	6.5	-0.4	1
Pakistan	51.5	66.4	14.9	0
Panama	55.8	60.3	4.5	0
Paraguay	44.7	57.7	13.0	0
Peru	51.6	57.7	6.0	1
Philippines	48.5	48.2	-0.3	0
Poland	60.5	62.8	2.2	0
Portugal	43.2	46.0	2.8	1
Romania	31.4	38.8	7.4	0
Russian Federation	39.9	47.6	7.7	0
Saudi Arabia	51.6	45.3	-6.3	0
Serbia	24.9	35.6	10.7	0
Singapore	28.7	38.3	9.6	0
Slovak Republic	27.8	33.2	5.4	0
Slovenia	27.3	36.0	8.7	0
South Africa	70.7	74.3	3.6	0
Spain	18.1	16.8	-1.3	1
Sri Lanka	58.6	60.0	1.4	0
Sweden	9.8	11.3	1.5	1
Switzerland	17.6	14.0	-3.6	0
Taiwan, China	38.2	39.2	1.0	0
Thailand	48.0	53.8	5.9	0
Trinidad and Tobago	39.2	39.1	0.0	0
Tunisia	60.2	63.2	3.0	0
Turkey	32.9	29.5	-3.4	0
Turkmenistan	25.8	15.0	-10.8	0
Ukraine	23.3	27.3	3.9	0
United Arab Emirates	46.7	60.5	13.8	0
United Kingdom	18.9	22.1	3.1	1
United States	26.9	28.8	1.9	1
Uruguay	51.6	65.4	13.8	0
Venezuela, RB	53.1	49.2	-3.9	0

Notes: See Section 4 for definitions and details. Source: Global Findex 2017.

Figure A.3.1. Main source of money to deal with a financial shock. Percent of non-hand-to-mouth individuals

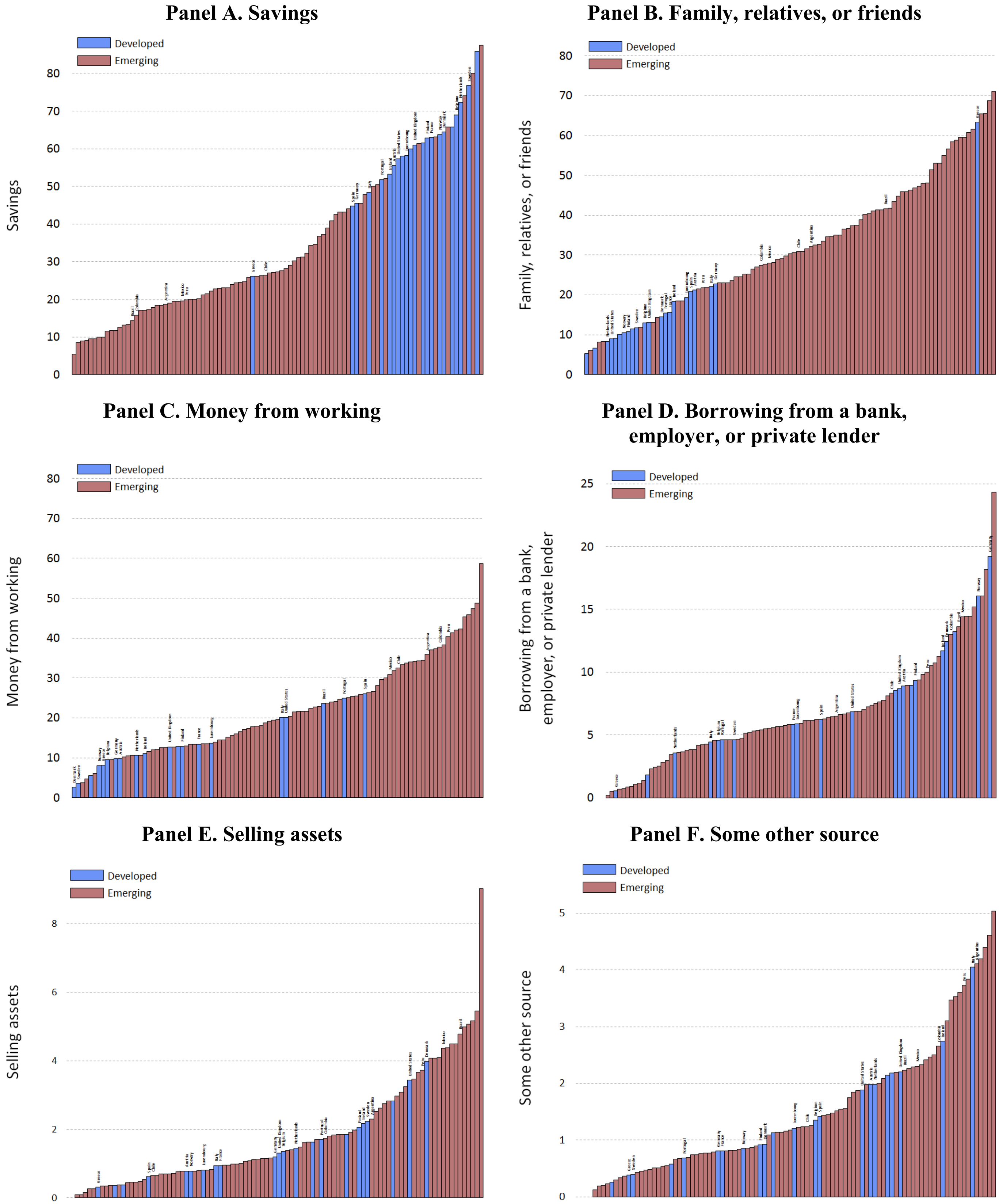
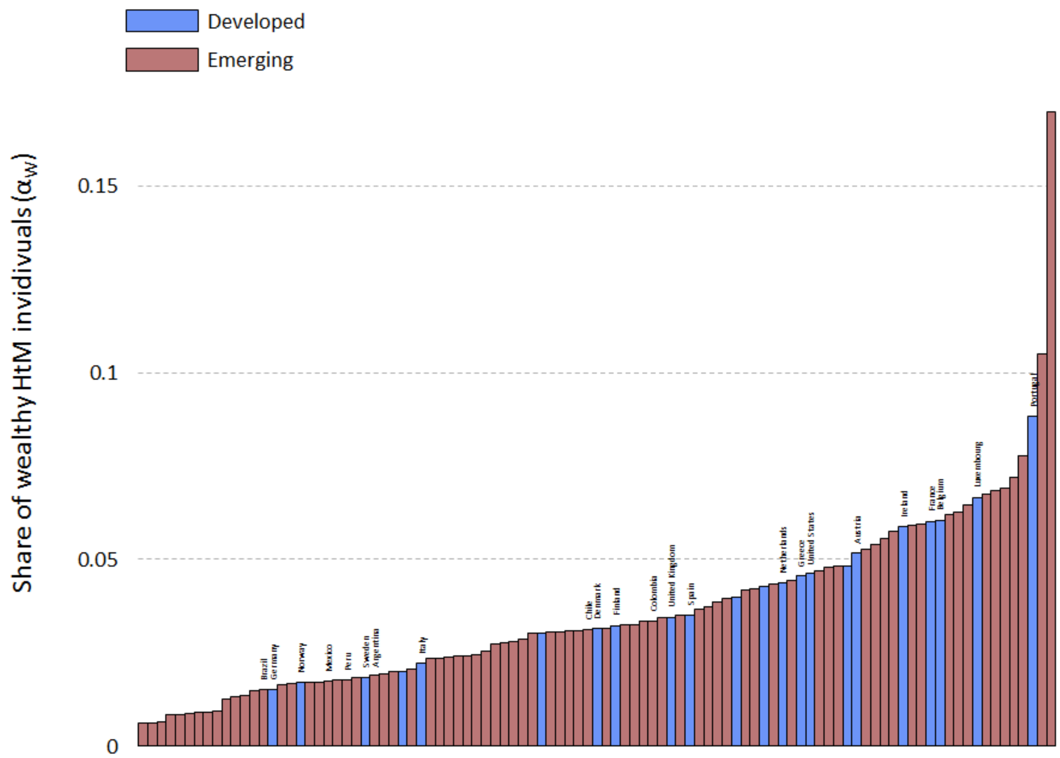


Figure A.3.2. Share of HtM individuals with and without property loans

Panal A. Share of HtM individuals with property loan



Panel B. Share of HtM individuals without property loan

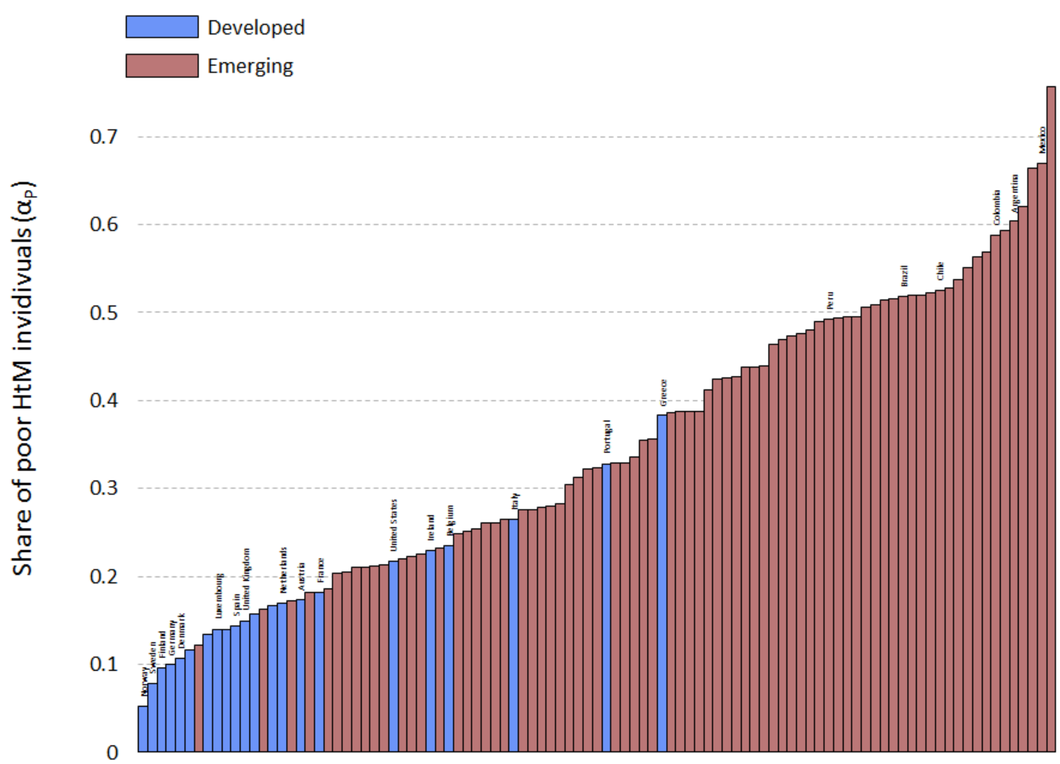


Table A.3.1. Share of hand-to-mouth individuals, by economic and demographic characteristics. Percent of respondents

	All (1)	Emerging (2)	Developed (3)
Unconditional average	37.9	43.0	17.8
Individual and household characteristics			
Household income			
Quintile 1	58.5	63.4	37.0
Quintile 2	47.0	53.0	23.1
Quintile 3	39.3	45.4	15.7
Quintile 4	31.9	36.8	13.1
Quintile 5	20.9	24.4	7.6
Education			
Primary or less	57.8	60.2	33.1
Secondary	35.7	40.1	19.6
Tertiary or more	17.9	21.9	8.7
Age			
15 to 34	38.9	41.6	21.7
35 to 54	36.7	41.3	17.4
55 to 64	37.2	44.2	15.5
65 and older	38.8	49.5	16.1
Sex			
Male	32.7	37.4	15.4
Female	42.3	47.7	20.0
Worforce			
No	44.9	50.6	20.6
Yes	33.5	38.0	16.1
Employment status			
Not employed	48.8	53.7	23.2
Employed	27.4	31.9	14.4

Table A.3.2. Probit regressions explaining HtM individual category with economic and demographic characteristics

	One characteristic at-a-time			All characteristics jointly		
Individual and household characteristics	All (1)	Emerging (2)	Developed (3)	All (4)	Emerging (5)	Developed (6)
Household income (omitted category: quintile 3)						
Quintile 1	0.52***	0.48***	0.70***	0.46***	0.41***	0.63***
	[39.0]	[33.0]	[21.6]	[32.3]	[26.3]	[18.7]
Quintile 2	0.11***	0.10***	0.14***	0.09***	0.09***	0.12***
	[16.9]	[14.6]	[8.8]	[13.8]	[11.7]	[7.4]
Quintile 4	-0.06***	-0.06***	-0.04***	-0.04***	-0.05***	-0.03***
	[-17.3]	[-17.0]	[-4.2]	[-12.7]	[-12.6]	[-3.1]
Quintile 5	-0.12***	-0.12***	-0.09***	-0.09***	-0.10***	-0.07***
	[-46.1]	[-44.5]	[-13.1]	[-33.9]	[-32.6]	[-9.7]
R^2	0.07	0.07	0.06			
Education (omitted category: secondary)						
Primary or less	0.51***	0.52***	0.37***	0.34***	0.34***	0.33***
	[48.5]	[47.0]	[12.1]	[30.0]	[27.5]	[10.1]
Tertiary or more	-0.54***	-0.55***	-0.52***	-0.37***	-0.37***	-0.35***
	[-45.0]	[-40.4]	[-20.0]	[-28.6]	[-25.6]	[-12.5]
R^2	0.08	0.07	0.04			
Age (omitted category: 35 to 54)						
15 to 34	-0.02**	-0.05***	0.18***	-0.02**	-0.04***	0.06*
	[-2.5]	[-4.8]	[6.6]	[-2.3]	[-3.1]	[1.9]
55 to 64	0.10***	0.14***	-0.04	0.04***	0.06***	-0.04
	[8.0]	[9.5]	[-1.2]	[3.0]	[3.9]	[-1.2]
65 and older	0.24***	0.33***	-0.01	0.01	0.09***	-0.22***
	[19.5]	[23.0]	[-0.2]	[0.6]	[5.2]	[-6.1]
R^2	0.01	0.01	0.01			
Sex (omitted category: male)						
Female	0.25***	0.26***	0.19***	0.15***	0.15***	0.12***
	[30.0]	[28.8]	[9.1]	[16.2]	[15.2]	[5.7]
R^2	0.01	0.01	0.01			
Worforce (omitted category: No)						
Yes	-0.33***	-0.36***	-0.18***	0.03***	0.04***	-0.03
	[-39.5]	[-39.3]	[-8.5]	[2.6]	[2.7]	[-0.8]
R^2	0.01	0.02	0.01			
Employment status (omitted category: not employed)						
Employed	-0.51***	-0.55***	-0.31***	-0.33 ***	-0.34***	-0.25***
	[-59.0]	[-58.0]	[-14.8]	[-28.3]	[-27.6]	[-8.1]
R^2	0.05	0.05	0.01	0.14	0.14	0.09

Table A.4.1. On-impact STMs values using benchmark calibration and combinations of α and θ which are allowed to vary between 0 and 1

α \ θ	0.00	0.05	0.10	0.15	0.20	0.25	0.30	0.35	0.40	0.45	0.50	0.55	0.60	0.65	0.70	0.75	0.80	0.85	0.90	0.95	1.00
0.0001	0.00	0.03	0.07	0.10	0.13	0.16	0.20	0.23	0.26	0.29	0.33	0.36	0.39	0.43	0.46	0.49	0.52	0.56	0.59	0.62	0.65
0.05	0.00	0.03	0.07	0.10	0.14	0.17	0.21	0.24	0.27	0.31	0.34	0.38	0.41	0.45	0.48	0.51	0.55	0.58	0.62	0.65	0.69
0.10	0.00	0.04	0.07	0.11	0.14	0.18	0.22	0.25	0.29	0.32	0.36	0.40	0.43	0.47	0.50	0.54	0.58	0.61	0.65	0.68	0.72
0.15	0.00	0.04	0.08	0.11	0.15	0.19	0.23	0.27	0.30	0.34	0.38	0.42	0.45	0.49	0.53	0.57	0.61	0.64	0.68	0.72	0.76
0.20	0.00	0.04	0.08	0.12	0.16	0.20	0.24	0.28	0.32	0.36	0.40	0.44	0.48	0.52	0.56	0.60	0.64	0.68	0.72	0.76	0.80
0.25	0.00	0.04	0.08	0.13	0.17	0.21	0.25	0.30	0.34	0.38	0.42	0.47	0.51	0.55	0.59	0.63	0.68	0.72	0.76	0.80	0.85
0.30	0.00	0.04	0.09	0.13	0.18	0.22	0.27	0.31	0.36	0.40	0.45	0.49	0.54	0.58	0.63	0.67	0.72	0.76	0.81	0.85	0.90
0.35	0.00	0.05	0.10	0.14	0.19	0.24	0.29	0.34	0.38	0.43	0.48	0.53	0.57	0.62	0.67	0.72	0.77	0.81	0.86	0.91	0.96
0.40	0.00	0.05	0.10	0.15	0.21	0.26	0.31	0.36	0.41	0.46	0.51	0.56	0.62	0.67	0.72	0.77	0.82	0.87	0.92	0.97	1.03
0.45	0.00	0.06	0.11	0.17	0.22	0.28	0.33	0.39	0.44	0.50	0.55	0.61	0.66	0.72	0.77	0.83	0.88	0.94	0.99	1.05	1.10
0.50	0.00	0.06	0.12	0.18	0.24	0.30	0.36	0.42	0.48	0.54	0.60	0.66	0.72	0.78	0.84	0.89	0.95	1.01	1.07	1.13	1.19
0.55	0.00	0.06	0.13	0.19	0.26	0.32	0.39	0.45	0.52	0.58	0.65	0.71	0.78	0.84	0.91	0.97	1.04	1.10	1.17	1.23	1.30
0.60	0.00	0.07	0.14	0.21	0.29	0.36	0.43	0.50	0.57	0.64	0.71	0.78	0.86	0.93	1.00	1.07	1.14	1.21	1.28	1.35	1.43
0.65	0.00	0.08	0.16	0.24	0.32	0.39	0.47	0.55	0.63	0.71	0.79	0.87	0.95	1.03	1.10	1.18	1.26	1.34	1.42	1.50	1.58
0.70	0.00	0.09	0.18	0.26	0.35	0.44	0.53	0.62	0.71	0.79	0.88	0.97	1.06	1.15	1.24	1.32	1.41	1.50	1.59	1.68	1.77
0.75	0.00	0.10	0.20	0.30	0.40	0.50	0.60	0.70	0.80	0.90	1.00	1.10	1.20	1.30	1.40	1.50	1.60	1.70	1.80	1.91	2.01
0.80	0.00	0.12	0.23	0.35	0.46	0.58	0.70	0.81	0.93	1.04	1.16	1.28	1.39	1.51	1.62	1.74	1.85	1.97	2.09	2.20	2.32
0.85	0.00	0.14	0.27	0.41	0.55	0.69	0.82	0.96	1.10	1.24	1.37	1.51	1.65	1.79	1.92	2.06	2.20	2.33	2.47	2.61	2.75
0.90	0.00	0.17	0.34	0.51	0.67	0.84	1.01	1.18	1.35	1.52	1.68	1.85	2.02	2.19	2.36	2.53	2.69	2.86	3.03	3.20	3.37
0.95	0.00	0.22	0.44	0.65	0.87	1.09	1.31	1.52	1.74	1.96	2.18	2.40	2.61	2.83	3.05	3.27	3.48	3.70	3.92	4.14	4.35
0.9999	0.00	0.31	0.62	0.93	1.24	1.54	1.85	2.16	2.47	2.78	3.09	3.40	3.71	4.02	4.32	4.63	4.94	5.25	5.56	5.87	6.18

Notes: Since the STM is not defined for α=0.00 and α=1.00, we selected α=0.0001 and α=0.9999, respectively. The shaded cells indicate combinations of α and θ such that STT<0. Recall that since STT ≡ θ-α, then STT<0 implies that α > θ.

Table A.5.1. On-impact STMs values dropping extreme observations from BP_IV specification

Cumulative Percentile Dopped from the Tails	STM(t)	Std_Errors	T_Stats	Obs
1%	0.419	0.129	3.24	1584
2%	0.395	0.126	3.11	1566
3%	0.423	0.131	3.21	1543

Table A.5.2. On-impact STMs values dropping one country at a time from BP_IV specification

Country Excluded	STM(t)	Std_Errors	T_Stats
Argentina	0.346	0.156	2.223
Austria	0.396	0.167	2.365
Belgium	0.389	0.149	2.606
Brazil	0.364	0.169	2.146
Chile	0.366	0.147	2.495
Colombia	0.409	0.148	2.771
Denmark	0.374	0.151	2.48
Finland	0.405	0.153	2.643
France	0.387	0.152	2.544
Germany	0.379	0.151	2.504
Greece	0.331	0.2	1.656
Ireland	0.489	0.095	5.152
Italy	0.391	0.152	2.579
Luxembourg	0.388	0.15	2.595
Mexico	0.391	0.149	2.623
Netherlands	0.384	0.153	2.508
Norway	0.355	0.15	2.358
Peru	0.39	0.158	2.471
Portugal	0.421	0.162	2.6
Spain	0.393	0.153	2.564
Sweden	0.381	0.154	2.466
United Kingdom	0.378	0.155	2.434
United States	0.418	0.152	2.741
	Mean	**Median**	**Stdv**
STM(t)	0.388	0.388	0.031

Table A.6.1. On-impact STMs values dropping extreme observations from BP_IV specification

Country	α	Θ	STT	**STM (baseline calibration)**	STM (baseline calibration, θ=100)	STM (baseline calibration, 5yrsZLB)	STM (baseline calibration, θ=100, 5yrsZLBy)	STM (baseline calibration, one-time ST shock)	STM (baseline calibration, one-time ST shock, θ=100)	STM (baseline calibration, one-time ST shock, 5yrsZLB)	STM (baseline calibration, one-time ST shock, θ=100, 5yrsZLB)
Austria	22.9	28.0	5.1	**0.23**	0.83	0.47	1.67	0.32	1.14	0.35	1.24
Belgium	29.9	29.3	-0.6	**0.26**	0.90	0.53	1.80	0.36	1.24	0.40	1.35
Denmark	13.9	15.6	1.8	**0.12**	0.75	0.24	1.52	0.16	1.04	0.18	1.13
Finland	12.9	14.2	1.3	**0.10**	0.74	0.21	1.50	0.15	1.03	0.16	1.12
France	24.4	29.4	5.0	**0.25**	0.84	0.50	1.68	0.34	1.16	0.37	1.26
Germany	11.7	18.5	6.8	**0.14**	0.73	0.28	1.49	0.19	1.02	0.20	1.11
Greece	43.9	48.2	4.3	**0.53**	1.09	1.04	2.15	0.72	1.50	0.79	1.63
Ireland	29.6	31.7	2.2	**0.29**	0.90	0.57	1.80	0.39	1.24	0.43	1.35
Italy	28.9	28.3	-0.6	**0.25**	0.89	0.50	1.78	0.35	1.23	0.38	1.33
Luxembourg	21.1	24.8	3.7	**0.20**	0.81	0.40	1.63	0.28	1.12	0.30	1.22
Netherlands	21.6	26.0	4.4	**0.21**	0.82	0.43	1.65	0.29	1.13	0.32	1.23
Norway	7.0	6.5	-0.4	**0.05**	0.70	0.09	1.42	0.06	0.97	0.07	1.05
Portugal	43.2	46.0	2.8	**0.49**	1.07	0.98	2.12	0.68	1.48	0.74	1.61
Romania	31.4	38.8	7.4	**0.35**	0.91	0.71	1.82	0.49	1.26	0.53	1.37
Spain	18.1	16.8	-1.3	**0.13**	0.78	0.27	1.58	0.18	1.08	0.20	1.18
Sweden	9.8	11.3	1.5	**0.08**	0.72	0.16	1.46	0.11	1.00	0.12	1.08
Switzerland	17.6	14.0	-3.6	**0.11**	0.78	0.22	1.58	0.15	1.08	0.16	1.18
United Kingdom	18.9	22.1	3.1	**0.17**	0.79	0.35	1.60	0.24	1.10	0.26	1.19
United States	26.9	28.8	1.9	**0.25**	0.87	0.50	1.74	0.35	1.20	0.37	1.30
Avg. Developed	**22.8**	**25.2**	**2.4**	**0.22**	**0.84**	**0.44**	**1.68**	**0.31**	**1.16**	**0.33**	**1.26**
Argentina	64.5	70.7	6.2	**1.12**	1.58	2.16	3.05	1.53	2.17	1.67	2.36
Brazil	53.9	56.6	2.7	**0.72**	1.28	1.42	2.50	1.00	1.76	1.08	1.91
Chile	56.6	64.8	8.2	**0.87**	1.35	1.71	2.63	1.20	1.85	1.31	2.02
Colombia	62.8	62.1	-0.7	**0.94**	1.51	1.82	2.94	1.29	2.08	1.41	2.27
Mexico	71.8	75.8	4.0	**1.40**	1.85	2.69	3.55	1.93	2.55	2.11	2.78
Peru	51.6	57.7	6.0	**0.71**	1.23	1.40	2.43	0.98	1.70	1.07	1.85
Average LAC	**60.2**	**64.6**	**4.4**	**0.96**	**1.47**	**1.87**	**2.85**	**1.32**	**2.02**	**1.44**	**2.20**
Difference	**37.4**	**39.4**	**2.0**	**0.74**	**0.63**	**1.42**	**1.17**	**1.02**	**0.86**	**1.11**	**0.94**