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André Teixeira, Zoë Venter

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1249-078 Lisboa,
Portugal

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Rua Miguel Lupi, 20
1249-078 LISBOA
Portugal

Telephone: +351 - 213 925 912
E-mail: rem@iseg.ulisboa.pt

https://rem.rc.iseg.ulisboa.pt/

Macroprudential Policy and Aggregate Demand*

André Teixeira† Zoë Venter‡

Abstract

This paper assesses the impact of macroprudential policy (MaPP) on aggregate demand in the EU between 2000-2019. Using a difference-in-differences approach, we find that MaPP reduces household consumption and increases firm investment. These effects are relatively mild in the short run but become more pronounced in the long run. Our findings point to a weaker macroeconomic impact than suggested in previous studies.

JEL Codes: E21; E22; E52; E58; O47.

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†Corresponding author. ISEG, Universidade de Lisboa; REM/UECE, R. Miguel Lúpi 20, 1249-078, Lisbon, Portugal. This work is supported by Fundação para a Ciência e a Tecnologia. Email: ateixeira@iseg.ulisboa.pt.

‡Universidade Católica Portuguesa, Palma de Cima, 1649-023, Lisbon, Portugal. Email: zventer@ucp.pt.

1 Introduction

Macroprudential policy (MaPP) is back in fashion, and rightly so. Few economists today would dispute that MaPP is a powerful weapon in the arsenal of crisis economics. But what do we know about its effects on aggregate demand? How does it affect consumption and investment? Answering these questions is crucial to assess the overall impact of MaPP.

So far, the existing literature has focused on the effects of MaPP on output (e.g., Lim et al., 2011; Cerutti et al., 2017). Not surprisingly, these studies find an inverse relationship between the adoption of MaPP and economic growth. Their story is intuitively simple but it has important implications: MaPP constrains credit with searing consequences on growth. This poses the question: should we evaluate the effectiveness of MaPP through the lens of output growth? After all, the goal of MaPP is to tame credit and slow down growth. Perhaps a more pertinent question to ask is whether MaPP affects households and firms in a similar way.

In this paper, we argue that the effects of MaPP on consumption and investment depend – directly or indirectly – on the financial constraints imposed on households and firms. If MaPP tightens borrowing constraints for everyone in the same way, both households and firms will be forced to save more and borrow less. This should lead to a decline in both consumption and investment. However, if MaPP makes access to credit more difficult for households than for firms, consumption is likely to fall but investment should remain stable or even increase if banks expand credit to the corporate sector. The converse could also be true: if MaPP makes access to credit more difficult for firms than for households, investment is likely to plummet and consumption should remain stable or even increase if banks shift their lending to households. In these last two scenarios, MaPP may have a profound effect on consumption and investment. By how much is an empirical issue, which we address via a novel difference-in-differences (DiD) approach.

The purpose of this paper is to extend the existing literature in three directions. First, we isolate the effects of MaPP on spending components of aggregate demand, particularly on consumption and investment. A shortcoming of previous papers is that they do not explain how MaPP influences private spending and undermines growth. Relative to these papers, we directly link the adoption of MaPP to fluctuations in household consumption and firm investment.

Second, we depart from traditional regressions and time series models to establish causality from MaPP to aggregate demand. This is important because MaPP is usually implemented in response to contemporaneous events. By using the first wide-scale staggered DiD in a policy setting, we are able to estimate the effects of MaPP in a setting with multiple countries and variation in treatment timing.

Finally, we distinguish between the short- and long-run effects of MaPP. Separating out the two is an empirically difficult matter, but we estimate a single interpretable treatment effect parameter that accounts for the dynamic effects of MaPP. This allows us to examine the effects of MaPP over time and determine whether they are more pronounced in the short or long run. This distinction between short- and long-run effects has received surprisingly little attention in the literature, but it is crucial to our understanding of the overall impact of MaPP.

In short, our results indicate that MaPP has asymmetric effects on consumption and investment. As we shall see, households in countries that implement MaPP increase their savings rate by 1.87-3.63 percentage points. This corresponds to a sharp increase of one quarter in savings. That said, we find that MaPP boosts firm investment by a whopping 5.05-6.63 percentage points over time. These results are statistically significant and stand up to several robustness checks.

The rest of the paper is organized as follows. Section 2 reviews the existing literature. Section 3 provides a detailed explanation of the staggered DiD. Section 4 discusses the empirical results and investigates the robustness of our findings. Section 5 concludes.

2 Literature Review

A vast literature examines the effects of MaPP on financial stability. Most of these papers suggest that MaPP curtails lending (Lim et al., 2011; Dell'Ariccia et al., 2012) and reduces excessive leverage (Claessens et al., 2012). Moreover, MaPP lessens the probability of a crisis (e.g., Kraft and Galac, 2011), especially in housing markets (Crowe et al., 2011; Kuttner and Shim, 2013). On the whole, the early literature provides compelling evidence that MaPP is an effective tool to manage financial cycles and reduce systemic risk.

However, recent research finds that MaPP may have deleterious effects on growth. Most notably, Angellini et al. (2014) and Elliott and Santos (2016) show that banking regulation decreases the steady state level of output. A few general equilibrium models also show that MaPP can be used to correct externalities in aggregate demand (e.g., Farhi and Werning, 2016). These results seem to be consistent with conventional theory on the relation between credit and spending. If MaPP restricts access to credit, it may force constrained households to reduce consumption (e.g., Hall, 2011). In a scenario of rapid deleveraging, MaPP may even increase precautionary savings, which is likely to depress aggregate demand even further (e.g., Eggertsson and Krugman, 2012; Guierrieri and Lorenzoni, 2017).

Much of this theoretical work finds empirical support in studies that use regressions and time series to estimate the effects of MaPP on growth (e.g., Lim et al., 2011; Akinci and Olmstead-Rumsey, 2015; Cerutti et al., 2017). This stream of research amassed a remarkable body of evidence on a negative relationship between MaPP and output growth. They generally conclude that MaPP should be tightened in boom periods and loosened in bust periods. Yet, these papers offer little explanation on the transmission channels of MaPP, i.e., the way in which MaPP is supposed to have affected output. This point is key to our understanding of the causal effects of MaPP on growth.

Until now, only a few empirical papers have used causal techniques to identify the impact of MaPP on growth. Behncke (2020) uses a simple DiD to estimate the effects of MaPP on lending using data from 25 banks in Switzerland. Her findings show that MaPP constrains lending with no unintended consequences on credit risk. But most papers point to important redistributive effects of MaPP. For example, DeFusco et al. (2020) use a DiD strategy to exploit a policy-induced discontinuity in the DSTI ratio in the US. They report a substantial increase in borrowing costs following the adoption of MaPP with ill effects on the distribution of leverage in the mortgage market. Interestingly, Acharya et al. (2020) also find a similar reallocation of mortgage credit after running a DiD model on loan level data from Ireland.

A major drawback of traditional DiD strategies is that they restrict the analysis to micro-level data from a single country. This is the simplest way to estimate the treatment effects of MaPP on credit. Although this DiD approach sheds light on the impact of MaPP on credit, it leaves many questions unanswered. For instance, how does MaPP affect spending across countries? How does the length of exposure to MaPP influence consumption and investment over time? By construction, traditional DiD approaches are unable to answer these questions because countries implement MaPP in different time periods.

Overall, there has been, in both theory and empirical work, an obvious push for generality on the effects of MaPP. Yet, it remains unclear how MaPP affects households and firms. The existing work is premised on the assumption that MaPP affects all agents in the same way. But this is unlikely because MaPP imposes different financial constraints on households and firms. A more interesting way to assess the overall impact of MaPP is to disentangle its causal effects on households and firms. It is to these matters that we turn next.

3 Methodology

3.1 Method

Our methodology is based on the DiD approach with staggered treatment adoption proposed by Callaway and Sant'Anna (2020). Similarly to a standard DiD, this method allows for a causal interpretation and it circumvents the restrictive assumptions of regressions and time series models. But unlike a standard DiD, it enables us to estimate the average treatment effects of MaPP in a setting with multiple countries and variation in treatment timing.

To do so, let us start with some notation. We consider τ periods where $t = 1, \ldots, \tau$ and that D_t is a binary variable that equals 1 when a country implements a macroprudential policy in quarter t and 0 otherwise. We then define G_g equal to 1 when a country is first treated in quarter g and 0 otherwise. Lastly, we assign C equal to 1 to the countries that never implement MaPP in our sample (i.e., "never-treated") and 0 otherwise. This implies that each country in our sample will have exactly one G_g or C equal to 1.

The generalized propensity score $p_g(X)$ is then defined as the probability that a country is treated conditional on having covariates X and belonging to group g or the control group, i.e., $p_g(X) = P(G_g = 1|X, G_g + C = 1)$. The observed outcome in each period t is estimated as follows:

$$Y_t = D_t Y_t(1) + (1 - D_t) Y_t(0) \tag{1}$$

where $Y_t(1)$ and $Y_t(0)$ are the potential outcomes in time t with and without treatment, respectively.

In contrast to a standard DiD, our main causal parameter of interest is a group-time average treatment effect($ATT(g, t)$). Simply put, the $ATT(g, t)$ gives us the average treatment effect experienced by group g in time t with "group" being defined as the first period of implementation of MaPP, as below:

$$ATT(g,t) = E[Y_t(1) - Y_t(0)|G_g = 1] \tag{2}$$

In our panel data setup, under the assumptions of parallel trends, irreversibility of treatment and covariate overlap and for $2 \leq g \leq t \leq \tau$, the $ATT(g,t)$ for group g in period t can be nonparametrically identified and estimated as below[1]:

$$ATT(g,t) = E\left[\left(\frac{G_g}{E[G_g]} - \frac{\frac{p_g(X)C}{1-p_g(X)}}{E\frac{p_g(X)C}{1-p_g(X)}}\right)(Y_t - Y_{g-1})\right] \tag{3}$$

Equation (3) allows us to assess how the effect of MaPP varies by group and time. It is worth noting that the $ATT(g,t)$ weights up observations from the control group that share similar characteristics to those in each treated group. This reweighting procedure ensures that the covariates of the treated group and the control group remain balanced.

Next, we aggregate the $ATT(g,t)$ across g and t to interpret the overall effects of MaPP. Given that many, if not most, treated groups will comprise a single country, the easiest way to obtain an "overall" $ATT(g,t)$ is to use a simple average, as follows:

$$\frac{2}{\tau(\tau-1)}\sum_{g=2}^{\tau}\sum_{t=2}^{\tau} 1\{g \leq t\} ATT(g,t) \tag{4}$$

Alternatively, we can compute a weighted average of each $ATT(g,t)$ by putting more weight on the $ATT(g,t)$ of groups that are exposed to MaPP for longer, as below:

$$\frac{1}{k}\sum_{g=2}^{\tau}\sum_{t=2}^{\tau} 1\{g \leq t\} ATT(g,t) P(G=g) \tag{5}$$

[1] Callaway and Sant'Anna (2020) show that Eq. (3) enables us to identify the treatment effects under the assumptions of parallel trends, irreversibility of treatment and covariate overlap. The first assumption was tested using the Cramér-von-Mises (CvM) test that fails to reject the parallel trends (Appendix D). The second assumption states that a country that adopts MaPP is forever treated. This is consistent with the behaviour of the countries in our sample that rarely reverse MaPP. The last assumption means that we need to ensure a control group for every treatment period and this is always the case in our estimations.

where $k = \sum_{g=2}^{\tau} \sum_{t=2}^{\tau} 1\{g \leq t\} P(G = g)$ so that the weights on the $ATT(g,t)$ sum to 1.

In our baseline model, the results are computed using the doubly robust method[2], no covariates and a "not yet treated" control group. Statistical significance is assessed using clustered bootstrapped standard errors at the country level, which also account for the autocorrelation of the data.

Of course, making inference based on several $ATT(g,t)$ can be troublesome. In the following subsections, we explain how the choice and timing of MaPP can bias the estimates of the overall $ATT(g,t)$. We then describe in detail how we estimate the treatment effect parameters to circumvent these issues. This can be done by computing group-time treatment effects and dynamic effects.

3.1.1 Group-time Treatment Effects

The adoption of MaPP is a choice of each country. Therefore, countries that implement MaPP earlier may also experience the effects of being treated earlier. A caveat of combining the $ATT(g,t)$ across g and t using a simple average is that we may overweight the effect of early-treated groups with more observations in post-treatment periods. To get around this issue, we compute the $ATT(g,t)$ specific to each treated group and we average them across all post-treatment periods:

$$\tilde{\theta}_S(g) = \frac{1}{\tau - g + 1} \sum_{t=2}^{\tau} 1\{g \leq t\} ATT(g,t) \tag{6}$$

Equation (6) is the time-averaged treatment effect for countries in group g. In simple terms, it is an average of each available $ATT(g,t)$ in a particular group g across time. The "overall" ATT, θ_S, can then be estimated by aggregating the group-specific treatment effects across groups, as below:

[2]The ATT uses OLS regression to compute the difference between the treated and the control groups for each observation; these differences are then weighted according to the probability of each observation occurring.

$$\theta_S = \sum_{g=2}^{\tau} \tilde{\theta}_S(g) P(G = g) \tag{7}$$

Equation (7) is our main measure of the overall impact of MaPP on aggregate demand. Although it may seem similar to equation (5), there is an important difference in the weights. While equation (5) assigns more weight to groups with a higher number of post-treatment periods, the weights in equation (7) depend only on group size. In this way, equation (7) does not overweight the effects of earlier-treated groups and provides an unbiased estimate of the effects of MaPP on each treated group g.

3.1.2 Dynamic Treatment Effects

The effects of MaPP on aggregate demand may also depend on the length of exposure to these policies. One may expect larger effects of MaPP to occur in longer horizons when households and firms have had the time to adjust their behaviour. However, a caveat of parameter (5) is that it does not explicitly consider a country's length of exposure to MaPP. To account for this, we begin by averaging the group-time $ATT(g, t)$ into treatment effects at different lengths of exposure to treatment, as follows:

$$\tilde{\theta}_D(e) = \sum_{g=2}^{\tau} \sum_{t=2}^{\tau} 1\{t - g + 1 = e\} ATT(g, t) P(G = g | t - g + 1 = e) \tag{8}$$

where e is the length of exposure to treatment.

A length of exposure equal to 0 estimates the average effect of MaPP across groups in the quarter of implementation of MaPP. To make the point most clearly, suppose that $e = 1$. Then, equation (8) estimates a value for the $ATT(g, t)$ based on group size for $g = t = 0$. This will be the estimate of the $ATT(g, t)$ in the first quarter after MaPP adoption. When $e = 2$, equation (8) estimates a different value for the $ATT(g, t)$ based on group size for all groups where $t - g = 1$. This will be the estimate of the $ATT(g,t)$ for all the countries exposed to MaPP for 2 quarters. The $ATT(g,t)$ is computed iteratively in this way for $e = 0, \ldots, 40$.

Then, the θ_D captures the dynamic evolution of treatment effects by averaging $\tilde{\theta}_D$ over all possible values of e, as below:

$$\theta_D = \frac{1}{\tau - 1} \sum_{e=1}^{\tau-1} \tilde{\theta}_D(e) \tag{9}$$

Equation (9) is our main estimate of the dynamic effects of MaPP. Once again, the crucial difference between θ_D, θ_S and equation (5) is in the weights: θ_D puts more emphasis on $ATT(g,t)$ when g is significantly less than t (i.e., when e is large). This allows for groups with a longer exposure to MaPP to be weighted more when there is a relatively small number of groups with long periods of exposure. This parameter is particularly suitable to measure how the treatment effects of MaPP evolve over time.

3.2 Data

Our empirical setting uses quarterly data on 21 European countries spanning the period 2000:Q1 to 2019:Q4[3]. In our baseline model, the main variables of interest are the household savings rate and firm investment rate. These two measures are often compared and the data is readily available from Eurostat. In robustness checks, we also consider other proxies like household consumption to GDP and non-financial corporations (NFC) gross fixed capital formation (GFCF) to GDP.

To account for the adoption of MaPP, we assign to the treated group every country that implements a MaPP to reduce banks' exposure to household and firm risks. This includes the Loan-to-value (LTV) ratio, Debt-service-to-income (DSTI) ratio and loan restrictions[4]. This data was collected from the IMF iMaPP database

[3] Our initial dataset comprises the 27 member states of the EU plus the United Kingdom. We exclude Cyprus, Malta, Lithuania and Luxembourg due to severe swings in savings and investment. Additionally, Bulgaria, Greece and Romania are removed because data is missing in the pre-treatment or post-treatment periods.

[4] In a similar spirit to Lim et al. (2011), we focus on loan-targeted MaPP.

(Alam et al., 2019) and updated with information from the ECB Macroprudential Bulletins.

Most countries in our sample end up implementing MaPP at some point in time. This may raise concerns about the size and heterogeneity of our control group. For example, our control group may comprise only low-income or high-income economies with very different characteristics to an average country. As such, we force the control group in the baseline model to include countries that have "not yet" implemented MaPP. This increases the size of the control group at the expense of treatment heterogeneity. The remaining models use alternative specifications for the control group, the estimation method and the aggregation method.

Although EU countries are fairly homogeneous, there could be covariate-specific trends in aggregate demand across groups. In particular, the literature on the secular drivers of savings suggests that demographics and inequality could influence private spending[5]. To account for these factors, we run alternative specifications of our model including the dependency ratio and GDP per capita. Detailed descriptions of every variable are available in Appendix A.

4 Results

4.1 Main Results

Table 1 presents the estimates for the impact of MaPP on household savings. The bulk of the results indicate that MaPP leads to a surge in savings. In the baseline model, the group-time treatment effect of MaPP increases savings by 1.94 percentage points. This impact is also surprisingly consistent across models ranging from 1.87-2.41 percentage points. To be clear, this estimate for savings is not a

[5]Other potential drivers of savings may include government debt and unemployment. However, these factors are not explicitly included as control variables in the DiD because they also influence the choice of MaPP and could render our results invalid. That said, GDP per capita should partially capture these effects.

small number. The average savings rate in our sample is only 11.33%, which means that MaPP pushes savings up by approximately one quarter.

The vast majority of group-time treatment effects are statistically significant and they stand up to robustness checks that control for demographics and income. They also hold when we restrict the control group to "never treated" countries. When we control for demography and income, the group-time treatment effects are based on the assumption that only countries with similar dependency ratios and GDP per capita would follow a similar trend in savings in the absence of MaPP. The conditional results indicate that MaPP leads to a rise in savings of 2.12-2.41 percentage points. Altogether, both unconditional and conditional results suggest that households increase their savings over and above what they would have in the absence of MaPP.

An interesting question is whether the impact of MaPP on savings is more profound in the short or in the long run. This can be assessed by examining the dynamic effects of MaPP. Our results show that the impact on savings gets stronger as countries are exposed to MaPP for longer. When we consider the length of exposure, the dynamic impact of MaPP on savings ranges from 2.93-3.63 percentage points. This can be visually inspected in Figure 1, which depicts the dynamic impact of MaPP on savings under the assumption of unconditional parallel trends. The dynamic effect on savings remains positive across time and becomes stronger as the length of exposure to MaPP increases, especially after year three.

The uncanny finding that MaPP has a lower impact in the short run is not entirely new. A few papers that use regressions to estimate the effects of MaPP over a four-year window report a severe contraction in credit and output around year three (e.g., Borio and Shim, 2007; Richter et al., 2019). Our estimates now provide a potential explanation for the plunging output: households reduce their consumption and increase savings around year three.

Table 2 presents our estimates for the impact of MaPP on firm investment. The group-time treatment effects of MaPP on firm investment are somewhat more modest. Most of our models report a positive and significant impact on investment but a few of the estimates are not statistically significant. This is not unexpected because firms often plan their investments in advance. It may be the case that the effects of MaPP are mostly dynamic.

Not surprisingly, the results for the dynamic effects on investment are far more enlightening. Our estimates show that MaPP increases firm investment by 5.05-6.63 percentage points over time. This corresponds to an increase of more than one quarter in firm investment since the average investment rate in our sample is 23.94%. As before, Figure 2 displays the dynamic effects of MaPP on investment. This figure forcibly shows that the short-run effects on investment are relatively mild but they build up significantly with time. The firm investment picks up around year four, which suggests that firms are slower to adjust to MaPP than households. The dynamic effects on investment peak at 6.63 percentage points when we control for differences in income across countries.

In summary, our results suggest that MaPP increases firm investment at the expense of household consumption. The immediate effects of MaPP are relatively modest but they pick up in the long run. If we make a crude comparison between our estimates for savings and investment, firm investment increases twice as much as the decrease in household consumption. These results point to a weaker macroeconomic cost of MaPP than reported in previous papers.

4.2 Individual Policy Tools

In this section, we disaggregate the effects of each MaPP tool on aggregate demand. We hope to cast light on the tools that have the greatest impact on private spending. To study individual policy choices, we ensure that the treated countries have not yet implemented another MaPP at the time of treatment. We also examine only countries that implement one household- or firm-targeted policy to isolate the impact of this policy choice.

Tables 3 through 8 provide the estimations of the impact of LTV ratios, loan restrictions and DSTI ratios on household savings and firm investment. In Tables 3 and 6, we see that the implementation of LTV ratios results in a 3.39 and 3.83 percentage point increase in savings and investment, respectively. When looking at the dynamic effects, we find that implementing an LTV ratio pushes savings and investment up by 4.25 and 8.17 percentage points over time, respectively. The dynamic impact is statistically significant in all cases. In the case of group-time treatment effects, we lose some statistical significance for savings when we condition on GDP per capita. But even in this case the impact is positive, which is consistent with our main findings.

Tables 4 and 7 provide the estimates for the impact of loan restrictions on savings and investment, respectively. Briefly, we find that loan restrictions have little impact on savings and investment. A possible explanation for this result is that loan restrictions are more likely to affect emerging economies than advanced economies. This is because loan restrictions usually target foreign currency lending, certain types of liabilities and excessive leverage (e.g., Cerutti et al., 2017).

Lastly, Tables 5 and 8 show the impact of the DSTI ratio on savings and investment, respectively. The results indicate that the adoption of a DSTI ratio spurs savings by 7.64 percentage points. Over time, the dynamic effects of the DSTI ratio result in a marked increase in savings of 4.74-8.74 percentage points. Of course, one should interpret these numbers with caution because inference is based on small treated groups. But if our results are more than chance, the DSTI ratio has serious consequences for households. It literally pushes savings up and sends consumption sharply downward. Interestingly, the impact of the DSTI ratio on investment is nearly zero in our baseline model. If we condition on the dependency ratio and the GDP per capita, we obtain mixed results but the impact on investment is always relatively meagre. Overall, the DSTI ratio has a greater impact on consumption than on investment.

Our bottom-line result is that measures that directly restrict access to credit – mainly the LTV and the DSTI ratio – seem to have a stronger impact on the spending components of aggregate demand. But their impact is also strikingly different: while the LTV ratio affects both household consumption and firm investment, the DSTI ratio has a greater effect on household consumption.

4.3 Robustness Checks

Our attempt to establish robustness takes two tacks. First, we test if our results are robust to alternative proxies for the dependent variables. In doing so, we provide reassuring evidence on the validity of our results. Second, we check if our results hold when we restrict the sample to include only countries that never loosen or remove MaPP. This addresses the main limitation of the staggered DiD, which assumes that countries that adopt MaPP will never reverse these policies.

4.3.1 Alternative Dependent Variables

A potential concern with our analysis is that we only look at the effects of MaPP using a single measure of household savings and firm investment. To explicitly address this issue, we rerun the DiD on alternative proxies of spending, particularly on household consumption to GDP and NFC GFCF to GDP.

Tables 9 and 10 provide the estimations of the DiD using these alternative proxies. We find that household consumption is 0.67 percentage points lower than what it would have been in the absence of MaPP. The dynamic effects on consumption raise this number to 2.20-2.83 percentage points over time. These estimates are in the same ballpark as the ones obtained earlier. Some of these results have less statistical significance but they all point to a negative impact of MaPP on consumption in the short and long run. This ties in with our previous finding that household savings rise sharply in response to MaPP.

The impact on GFCF is also similar to before. Once again, the group-time average treatment effects on investment are close to zero but we do find strong dynamic effects. As the length of exposure to MaPP increases, the impact on GFCF becomes more pronounced. We estimate that the impact on investment can be as high as 3.95-4.98 percentage points. Perhaps more interestingly, we again find that investment only picks up three years after the adoption of MaPP. These results suggest that banks may need some time to adjust to new regulation or that agents may not be as forward-looking as previously thought. The underlying causes of the surge in investment are hard to pinpoint in our analysis, but one thing is clear: MaPP has a lower impact on investment in the short run than in the long run. This result is statistically significant and holds across all our model specifications. This is interesting because MaPP is often implemented in response to a shock. But perhaps this is already too late.

4.3.2 Restricted Sample

A caveat of our staggered DiD is the assumption that once a country is treated, it will remain treated throughout the sample period. This could bias the results if countries reverse MaPP at some point in time. To account for this possibility, we rerun our models using a restricted sample that includes only countries that never loosen or remove MaPP[6].

Tables 11 and 12 show the estimations of the DiD using the restricted sample. In general, our results continue to hold throughout. They show that, on average, households save between 1.96-2.74 percentage points more than they would have in the absence of MaPP. The dynamic impact suggests an increase of up to 4 percentage points over time, particularly after three years of exposure to MaPP as shown in Figure 3. This matches all our previous findings.

[6]Only Denmark, The Netherlands and Poland remove or loosen a MaPP during our sample period. These countries are excluded from this restricted sample.

Turning to investment, one gratifying result is that our estimates become more statistically significant in the restricted sample. The group-time average treatment effect is now statistically significant in half of our models with an estimated impact of 0.62-1.14 percentage points. The dynamic effects of MaPP indicate that investment increases by 6.78-8.22 percentage points, which is only slightly higher than the impact found in the main results. When we plot the dynamic effects in Figure 4, we can see that GFCF starts to rise significantly after year four, which is also in line with the pattern of the firm investment rate. This is reassuring in spite of the fact that we use a different sample.

5 Conclusions

In this paper, we have investigated the causal effects of MaPP on aggregate demand. Using a novel DiD approach with staggered adoption, we find that MaPP reduces household consumption in the short and long run, while increasing firm investment in the long run. These results clarify a point that is too often overlooked in the literature: consumption and investment are important transmission channels through which MaPP affects growth.

But why does MaPP hinder consumption and facilitate investment? We believe the answer lies in the type of financial constraint imposed by MaPP. When we look at individual MaPP tools, we find that the LTV and the DSTI ratio have a deleterious impact on household consumption but the LTV ratio has a positive effect on firm investment. A potential explanation is that LTV ratios target mainly home loans. This is likely to foster financial stability, which may lead to a surge in investment at the cost of lower consumption. Finally, we find little evidence that loan restrictions affect aggregate demand, at least, in advanced economies.

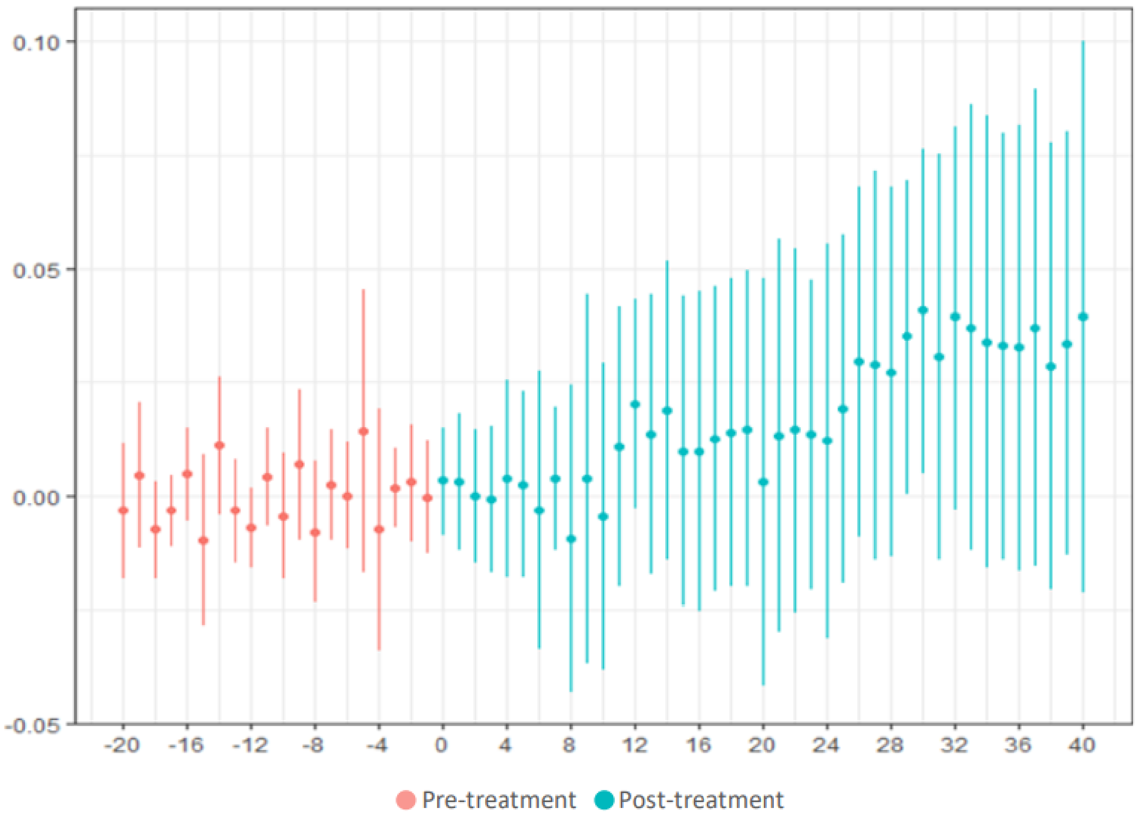
Some limitations of our model point to potential research opportunities. First, the staggered DiD assumes that a country becomes forever treated after implementing a MaPP. An unintended consequence is that we cannot fully capture the effects of loosening, tightening or removing a MaPP. We address this caveat by rerunning our model on a restricted sample of countries that never loosen or remove MaPP. It would also be interesting to assess how changes in the overall macroprudential stance affect consumption and investment.

Second, our results provide suggestive evidence that some MaPP tools have a disproportionally high impact on aggregate demand. Yet, we are unable to fully disaggregate the effects of individual tools because most of the countries in our sample implement DSTI ratios in conjunction with LTV ratios or loan restrictions. Understanding how the design of MaPP influences aggregate demand remains a potentially fruitful area for research.

In spite of these caveats, our results offer useful policy guidance. An important finding is that MaPP has a weaker macroeconomic cost than previously suggested in the literature. If left unattended, MaPP can have pernicious effects on consumption; but if properly managed, MaPP can also lead to higher investment over time. The overall macroeconomic impact, then, depends on a country's policy objectives. If private consumption is in a free fall, MaPP may aggravate the consequences for households, particularly if countries implement LTV and DSTI ratios. But if private consumption is relatively stable, then MaPP can be an effective tool to restore financial stability and boost investment in the long run.

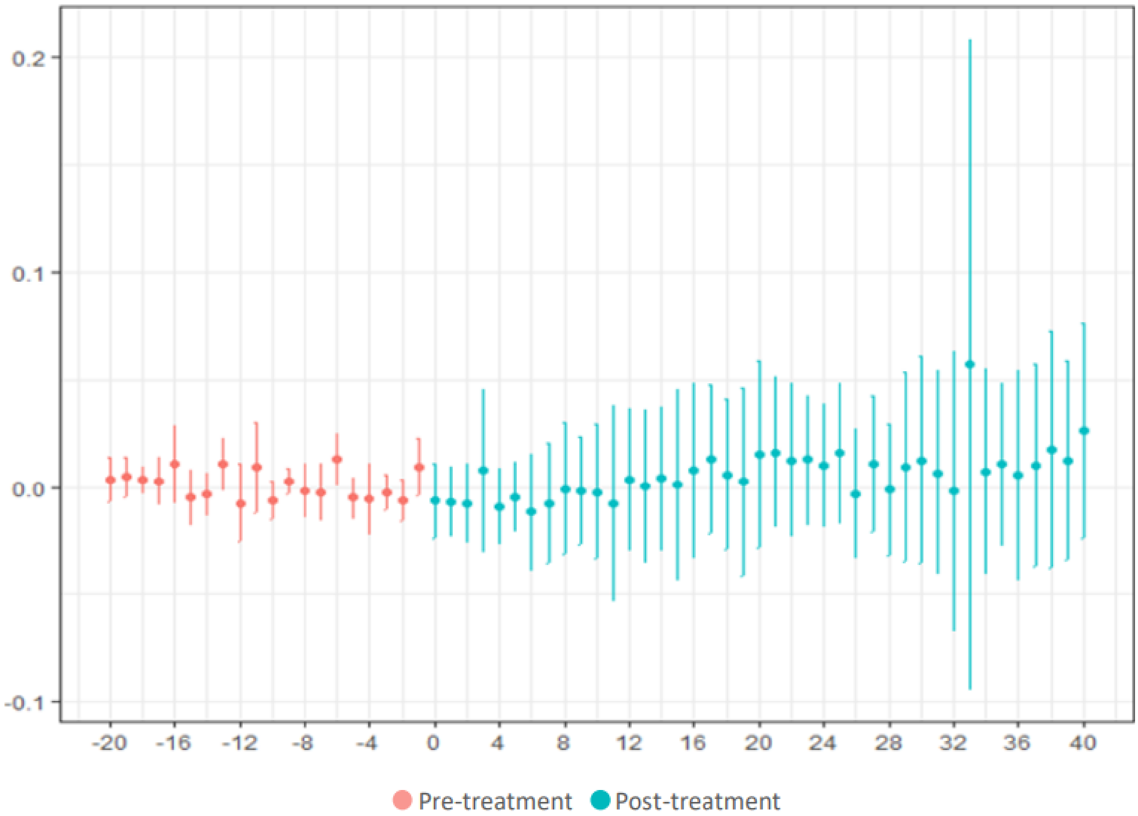
Another important finding is that the effects of MaPP on aggregate demand seem to only gain traction after three years. This finding is interesting because MaPP is usually tightened in response to a crisis but our results suggest that this is already too late. Indeed, MaPP may only send demand downward at the height of the crisis. Rather, our results support the view that policy makers should continuously adjust MaPP in much the same way as monetary policy. But given that MaPP has the ability to drive spending, policy makers should also be cautious about using it liberally.

Figure 1: Dynamic Impact of MaPP on Household Savings Rate, 2000-2019



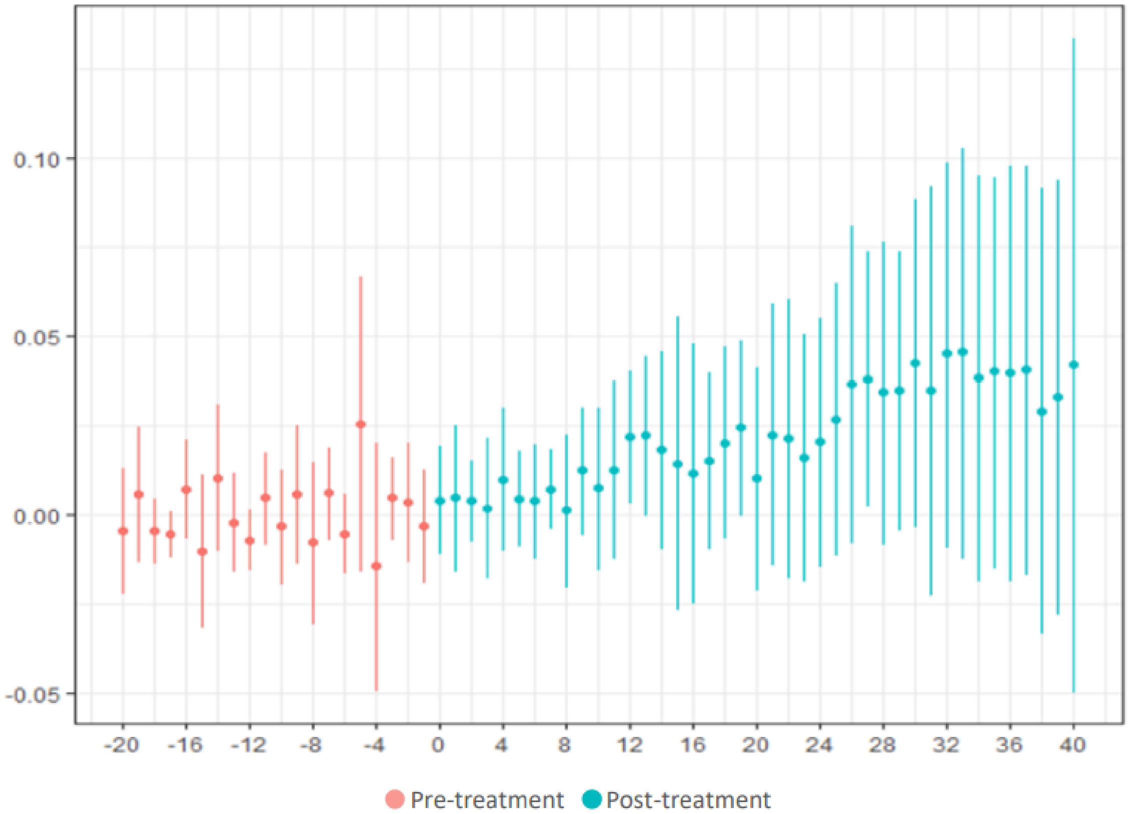
Note: The x-axis is the length of exposure to the treatment. A length of exposure equal to 0 corresponds to the average effect of implementing macroprudential policy across groups in the period they first implement macroprudential policy; equal to -1 corresponds to the period before groups implement macroprudential policy and equal to 1 corresponds to the first period after initial implementation.

Figure 2: Dynamic Impact of MaPP on Firm Investment Rate, 2000-2019



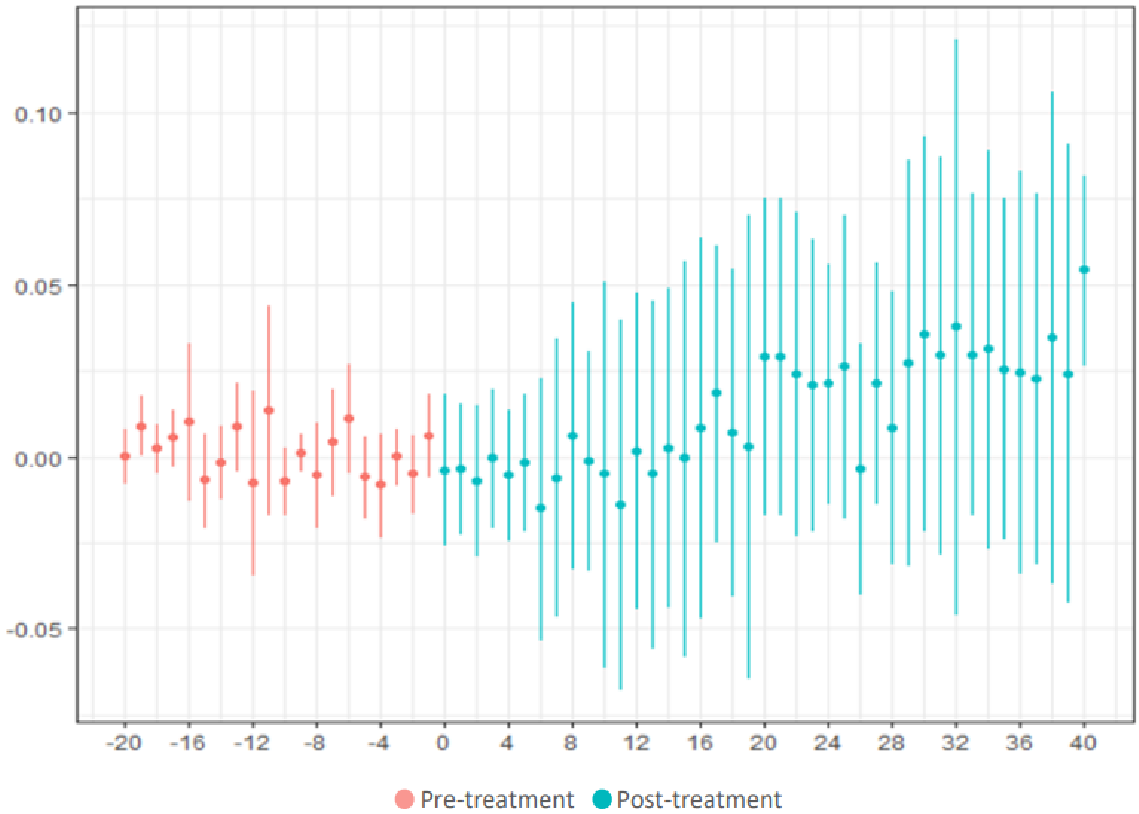
Note: The x-axis is the length of exposure to the treatment. A length of exposure equal to 0 corresponds to the average effect of implementing macroprudential policy across groups in the period they first implement macroprudential policy; equal to -1 corresponds to the period before groups implement macroprudential policy and equal to 1 corresponds to the first period after initial implementation.

Figure 3: Dynamic Impact of MaPP on Household Savings Rate, Restricted Sample, 2000-2019



Note: The x-axis is the length of exposure to the treatment. A length of exposure equal to 0 corresponds to the average effect of implementing macroprudential policy across groups in the period they first implement macroprudential policy; equal to -1 corresponds to the period before groups implement macroprudential policy and equal to 1 corresponds to the first period after initial implementation.

Figure 4: Dynamic Impact of MaPP on Firm Investment Rate, Restricted Sample, 2000-2019



Note: The x-axis is the length of exposure to the treatment. A length of exposure equal to 0 corresponds to the average effect of implementing macroprudential policy across groups in the period they first implement macroprudential policy; equal to -1 corresponds to the period before groups implement macroprudential policy and equal to 1 corresponds to the first period after initial implementation.

Table 1: **Impact of MaPP on Household Savings Rate, 2000-2019**

Model	**I**	**II**	**III**	**IV**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Not Yet Treated	Not Yet Treated	Never Treated
Estimation Method	Doubly Robust	Regression	Regression	Doubly Robust
Aggregation Method	Group	Group	Group	Group
Covariates	-	Dependency Ratio	GDP per capita	-
ATT	0.0194**	0.0232**	0.0241**	0.0187**
Standard Error	0.0053	0.0060	0.0062	0.0059
Model	**V**	**VI**	**VII**	**VIII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Never Treated	Never Treated	Not Yet Treated	Not Yet Treated
Estimation Method	Regression	Regression	Doubly Robust	Regression
Aggregation Method	Group	Group	Dynamic	Dynamic
Covariates	Dependency Ratio	GDP per capita	-	Dependency Ratio
ATT	0.0212**	0.0119	0.0302**	0.0363**
Standard Error	0.0080	0.0085	0.0153	0.0180
Model	**IX**	**X**	**XI**	**XII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Never Treated	Never Treated	Never Treated
Estimation Method	Regression	Doubly Robust	Regression	Regression
Aggregation Method	Dynamic	Dynamic	Dynamic	Dynamic
Covariates	GDP per capita	-	Dependency Ratio	GDP per capita
ATT	0.0224	0.0293*	0.0332*	0.0064
Standard Error	0.0171	0.0167	0.0197	0.0221

Note: The table reports the aggregated group treatment effect (ATT(g,t)) parameters estimated as in Eq. (7) to evaluate the impact of MaPP on savings across groups. The aggregated dynamic treatment effect parameters estimated as in Eq. (9) are also reported to examine the impact of MaPP on savings over time. ATT(g,t) is the average treatment effect experienced by group g in time t. Statistical significance is assessed using clustered bootstrapped standard errors at the country level that also account for the autocorrelation of the data. "**" represents statistical significance at a 5% level and "*" represents statistical significance at a 10% level.

Table 2: Impact of MaPP on Firm Investment Rate, 2000-2019

Model	**I**	**II**	**III**	**IV**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Not Yet Treated	Not Yet Treated	Never Treated
Estimation Method	Doubly Robust	Regression	Regression	Doubly Robust
Aggregation Method	Group	Group	Group	Group
Covariates	-	Dependency Ratio	GDP per capita	-
ATT	0.0074**	0.0006	0.0062	0.0068**
Standard Error	0.0030	0.0034	0.0050	0.0021
Model	**V**	**VI**	**VII**	**VIII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Never Treated	Never Treated	Not Yet Treated	Not Yet Treated
Estimation Method	Regression	Regression	Doubly Robust	Regression
Aggregation Method	Group	Group	Dynamic	Dynamic
Covariates	Dependency Ratio	GDP per capita	-	Dependency Ratio
ATT	0.0021	0.0165**	0.0591**	0.0505*
Standard Error	0.0031	0.0053	0.0260	0.0274
Model	**IX**	**X**	**XI**	**XII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Never Treated	Never Treated	Never Treated
Estimation Method	Regression	Doubly Robust	Regression	Regression
Aggregation Method	Dynamic	Dynamic	Dynamic	Dynamic
Covariates	GDP per capita	-	Dependency Ratio	GDP per capita
ATT	0.0534**	0.0575**	0.0525**	0.0663**
Standard Error	0.0231	0.0239	0.0238	0.0262

Note: The table reports the aggregated group treatment effect (ATT(g,t)) parameters estimated as in Eq. (7) to evaluate the impact of MaPP on investment across groups. The aggregated dynamic treatment effect parameters estimated as in Eq. (9) are also reported to examine the impact of MaPP on investment over time. ATT(g,t) is the average treatment effect experienced by group g in time t. Statistical significance is assessed using clustered bootstrapped standard errors at the country level that also account for the autocorrelation of the data. "**" represents statistical significance at a 5% level and "*" represents statistical significance at a 10% level.

Table 3: Impact of MaPP on Household Savings Rate, LTV, 2000-2019

Model	**I**	**II**	**III**	**IV**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Not Yet Treated	Not Yet Treated	Never Treated
Estimation Method	Doubly Robust	Regression	Regression	Doubly Robust
Aggregation Method	Group	Group	Group	Group
Covariates	-	Dependency Ratio	GDP per capita	-
ATT	0.0339**	0.0413**	0.0153	0.0331**
Standard Error	0.0065	0.0050	0.0120	0.0072
Model	**V**	**VI**	**VII**	**VIII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Never Treated	Never Treated	Not Yet Treated	Not Yet Treated
Estimation Method	Regression	Regression	Doubly Robust	Regression
Aggregation Method	Group	Group	Dynamic	Dynamic
Covariates	Dependency Ratio	GDP per capita	-	Dependency Ratio
ATT	0.0411**	0.0079	0.0425**	0.0528**
Standard Error	0.0068	0.0163	0.0217	0.0189
Model	**IX**	**X**	**XI**	**XII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Never Treated	Never Treated	Never Treated
Estimation Method	Regression	Doubly Robust	Regression	Regression
Aggregation Method	Dynamic	Dynamic	Dynamic	Dynamic
Covariates	GDP per capita	-	Dependency Ratio	GDP per capita
ATT	0.0086	0.0418*	0.0529**	0.0474**
Standard Error	0.0243	0.0221	0.0196	0.0183

Note: The table reports the aggregated group treatment effect (ATT(g,t)) parameters estimated as in Eq. (7) to evaluate the impact of MaPP on savings across groups. The aggregated dynamic treatment effect parameters estimated as in Eq. (9) are also reported to examine the impact of MaPP on savings over time. ATT(g,t) is the average treatment effect experienced by group g in time t. Statistical significance is assessed using clustered bootstrapped standard errors at the country level that also account for the autocorrelation of the data. "**" represents statistical significance at a 5% level and "*" represents statistical significance at a 10% level.

Table 4: Impact of MaPP on Household Savings Rate, Loan Restrictions, 2000-2019

Model	**I**	**II**	**III**	**IV**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Not Yet Treated	Not Yet Treated	Never Treated
Estimation Method	Doubly Robust	Regression	Regression	Doubly Robust
Aggregation Method	Group	Group	Group	Group
Covariates	-	Dependency Ratio	GDP per capita	-
ATT	0.0064	0.0033	0.0243	0.0066
Standard Error	0.0090	0.0178	0.0396	0.0090
Model	**V**	**VI**	**VII**	**VIII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Never Treated	Never Treated	Not Yet Treated	Not Yet Treated
Estimation Method	Regression	Regression	Doubly Robust	Regression
Aggregation Method	Group	Group	Dynamic	Dynamic
Covariates	Dependency Ratio	GDP per capita	-	Dependency Ratio
ATT	0.0035	0.0260	0.0055	0.0002
Standard Error	0.0173	0.0360	0.0106	0.0239
Model	**IX**	**X**	**XI**	**XII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Never Treated	Never Treated	Never Treated
Estimation Method	Regression	Doubly Robust	Regression	Regression
Aggregation Method	Dynamic	Dynamic	Dynamic	Dynamic
Covariates	GDP per capita	-	Dependency Ratio	GDP per capita
ATT	0.0264	0.0056	0.0004	0.0281
Standard Error	0.0512	0.0108	0.0247	0.0477

Note: The table reports the aggregated group treatment effect (ATT(g,t)) parameters estimated as in Eq. (7) to evaluate the impact of MaPP on savings across groups. The aggregated dynamic treatment effect parameters estimated as in Eq. (9) are also reported to examine the impact of MaPP on savings over time. ATT(g,t) is the average treatment effect experienced by group g in time t. Statistical significance is assessed using clustered bootstrapped standard errors at the country level that also account for the autocorrelation of the data. "**" represents statistical significance at a 5% level and "*" represents statistical significance at a 10% level.

Table 5: Impact of MaPP on Household Savings Rate, DSTI, 2000-2019

Model	**I**	**II**	**III**	**IV**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Not Yet Treated	Not Yet Treated	Never Treated
Estimation Method	Doubly Robust	Regression	Regression	Doubly Robust
Aggregation Method	Group	Group	Group	Group
Covariates	-	Dependency Ratio	GDP per capita	-
ATT	0.0764**	0.0849**	0.0874**	0.0764**
Standard Error	0.0076	0.0169	0.0122	0.0071
Model	**V**	**VI**	**VII**	**VIII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Never Treated	Never Treated	Not Yet Treated	Not Yet Treated
Estimation Method	Regression	Regression	Doubly Robust	Regression
Aggregation Method	Group	Group	Dynamic	Dynamic
Covariates	Dependency Ratio	GDP per capita	-	Dependency Ratio
ATT	0.0849**	0.0874**	0.0764**	0.0849**
Standard Error	0.0225	0.0202	0.0076	0.0169
Model	**IX**	**X**	**XI**	**XII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Never Treated	Never Treated	Never Treated
Estimation Method	Regression	Doubly Robust	Regression	Regression
Aggregation Method	Dynamic	Dynamic	Dynamic	Dynamic
Covariates	GDP per capita	-	Dependency Ratio	GDP per capita
ATT	0.0874**	0.0764**	0.0849**	0.0474**
Standard Error	0.0122	0.0071	0.0225	0.0202

Note: The table reports the aggregated group treatment effect (ATT(g,t)) parameters estimated as in Eq. (7) to evaluate the impact of MaPP on savings across groups. The aggregated dynamic treatment effect parameters estimated as in Eq. (9) are also reported to examine the impact of MaPP on savings over time. ATT(g,t) is the average treatment effect experienced by group g in time t. Statistical significance is assessed using clustered bootstrapped standard errors at the country level that also account for the autocorrelation of the data. "**" represents statistical significance at a 5% level and "*" represents statistical significance at a 10% level.

Table 6: Impact of MaPP on Firm Investment Rate, LTV, 2000-2019

Model	**I**	**II**	**III**	**IV**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Not Yet Treated	Not Yet Treated	Never Treated
Estimation Method	Doubly Robust	Regression	Regression	Doubly Robust
Aggregation Method	Group	Group	Group	Group
Covariates	-	Dependency Ratio	GDP per capita	-
ATT	0.0383**	0.0350**	0.0376**	0.0386**
Standard Error	0.0034	0.0041	0.0041	0.0037
Model	**V**	**VI**	**VII**	**VIII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Never Treated	Never Treated	Not Yet Treated	Not Yet Treated
Estimation Method	Regression	Regression	Doubly Robust	Regression
Aggregation Method	Group	Group	Dynamic	Dynamic
Covariates	Dependency Ratio	GDP per capita	-	Dependency Ratio
ATT	0.0351**	0.0385**	0.0817**	0.0787**
Standard Error	0.0051	0.0035	0.0243	0.0219
Model	**IX**	**X**	**XI**	**XII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Never Treated	Never Treated	Never Treated
Estimation Method	Regression	Doubly Robust	Regression	Regression
Aggregation Method	Dynamic	Dynamic	Dynamic	Dynamic
Covariates	GDP per capita	-	Dependency Ratio	GDP per capita
ATT	0.0828**	0.0820*	0.0787**	0.0835**
Standard Error	0.0281	0.0232	0.0217	0.0285

Note: The table reports the aggregated group treatment effect (ATT(g,t)) parameters estimated as in Eq. (7) to evaluate the impact of MaPP on investment across groups. The aggregated dynamic treatment effect parameters estimated as in Eq. (9) are also reported to examine the impact of MaPP on savings over time. ATT(g,t) is the average treatment effect experienced by group g in time t. Statistical significance is assessed using clustered bootstrapped standard errors at the country level that also account for the autocorrelation of the data. "**" represents statistical significance at a 5% level and "*" represents statistical significance at a 10% level.

Table 7: Impact of MaPP on Firm Investment Rate, Loan Restrictions, 2000-2019

Model	**I**	**II**	**III**	**IV**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Not Yet Treated	Not Yet Treated	Never Treated
Estimation Method	Doubly Robust	Regression	Regression	Doubly Robust
Aggregation Method	Group	Group	Group	Group
Covariates	-	Dependency Ratio	GDP per capita	-
ATT	0.0045	0.0054	0.0026	0.0045
Standard Error	0.0039	0.0048	0.0034	0.0042

Model	**V**	**VI**	**VII**	**VIII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Never Treated	Never Treated	Not Yet Treated	Not Yet Treated
Estimation Method	Regression	Regression	Doubly Robust	Regression
Aggregation Method	Group	Group	Dynamic	Dynamic
Covariates	Dependency Ratio	GDP per capita	-	Dependency Ratio
ATT	0.0054	0.0026	0.0045	0.0054
Standard Error	0.0037	0.0035	0.0039	0.0048

Model	**IX**	**X**	**XI**	**XII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Never Treated	Never Treated	Never Treated
Estimation Method	Regression	Doubly Robust	Regression	Regression
Aggregation Method	Dynamic	Dynamic	Dynamic	Dynamic
Covariates	GDP per capita	-	Dependency Ratio	GDP per capita
ATT	0.0026	0.0045	0.0054	0.0026
Standard Error	0.0034	0.0042	0.0037	0.0035

Note: The table reports the aggregated group treatment effect (ATT(g,t)) parameters estimated as in Eq. (7) to evaluate the impact of MaPP on savings across groups. The aggregated dynamic treatment effect parameters estimated as in Eq. (9) are also reported to examine the impact of MaPP on investment over time. ATT(g,t) is the average treatment effect experienced by group g in time t. Statistical significance is assessed using clustered bootstrapped standard errors at the country level that also account for the autocorrelation of the data. "**" represents statistical significance at a 5% level and "*" represents statistical significance at a 10% level.

Table 8: Impact of MaPP on Firm Investment Rate, DSTI, 2000-2019

Model	**I**	**II**	**III**	**IV**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Not Yet Treated	Not Yet Treated	Never Treated
Estimation Method	Doubly Robust	Regression	Regression	Doubly Robust
Aggregation Method	Group	Group	Group	Group
Covariates	-	Dependency Ratio	GDP per capita	-
ATT	0.0059	-0.0189*	0.0394**	0.0060
Standard Error	0.0052	0.0101	0.0028	0.0046
Model	**V**	**VI**	**VII**	**VIII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Never Treated	Never Treated	Not Yet Treated	Not Yet Treated
Estimation Method	Regression	Regression	Doubly Robust	Regression
Aggregation Method	Group	Group	Dynamic	Dynamic
Covariates	Dependency Ratio	GDP per capita	-	Dependency Ratio
ATT	-0.0192*	0.0389**	0.0088	-0.0146
Standard Error	0.0113	0.0029	0.0093	0.0162
Model	**IX**	**X**	**XI**	**XII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Never Treated	Never Treated	Never Treated
Estimation Method	Regression	Doubly Robust	Regression	Regression
Aggregation Method	Dynamic	Dynamic	Dynamic	Dynamic
Covariates	GDP per capita	-	Dependency Ratio	GDP per capita
ATT	0.0299**	0.0090	-0.0148	0.0294**
Standard Error	0.0131	0.0107	0.0167	0.0138

Note: The table reports the aggregated group treatment effect (ATT(g,t)) parameters estimated as in Eq. (7) to evaluate the impact of MaPP on savings across groups. The aggregated dynamic treatment effect parameters estimated as in Eq. (9) are also reported to examine the impact of MaPP on savings over time. ATT(g,t) is the average treatment effect experienced by group g in time t. Statistical significance is assessed using clustered bootstrapped standard errors at the country level that also account for the autocorrelation of the data. "**" represents statistical significance at a 5% level and "*" represents statistical significance at a 10% level.

Table 9: Impact of MaPP on Household Consumption to GDP, 2000-2019

Model	I	II	III	IV
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Not Yet Treated	Not Yet Treated	Never Treated
Estimation Method	Doubly Robust	Regression	Regression	Doubly Robust
Aggregation Method	Group	Group	Group	Group
Covariates	-	Dependency Ratio	GDP per capita	-
ATT	-0.0067*	-0.0084**	-0.0104**	-0.0050
Standard Error	0.0036	0.0033	0.0037	0.0033
Model	**V**	**VI**	**VII**	**VIII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Never Treated	Never Treated	Not Yet Treated	Not Yet Treated
Estimation Method	Regression	Regression	Doubly Robust	Regression
Aggregation Method	Group	Group	Dynamic	Dynamic
Covariates	Dependency Ratio	GDP per capita	-	Dependency Ratio
ATT	-0.0053*	-0.0037	-0.0247**	-0.0283**
Standard Error	0.0030	0.0069	0.0108	0.0117
Model	**IX**	**X**	**XI**	**XII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Never Treated	Never Treated	Never Treated
Estimation Method	Regression	Doubly Robust	Regression	Regression
Aggregation Method	Dynamic	Dynamic	Dynamic	Dynamic
Covariates	GDP per capita	-	Dependency Ratio	GDP per capita
ATT	-0.0156	-0.0220**	-0.0232**	-0.0037
Standard Error	0.0137	0.0109	0.0110	0.0169

Note: The table reports the aggregated group treatment effect (ATT(g,t)) parameters estimated as in Eq. (7) to evaluate the impact of MaPP on consumption to GDP across groups. The aggregated dynamic treatment effect parameters estimated as in Eq. (9) are also reported to examine the impact of MaPP on consumption to GDP over time. ATT(g,t) is the average treatment effect experienced by group g in time t. Statistical significance is assessed using clustered bootstrapped standard errors at the country level that also account for the autocorrelation of the data. "**" represents statistical significance at a 5% level and "*" represents statistical significance at a 10% level.

Table 10: Impact of MaPP on NFC GFCF to GDP, 2000-2019

Model	**I**	**II**	**III**	**IV**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Not Yet Treated	Not Yet Treated	Never Treated
Estimation Method	Doubly Robust	Regression	Regression	Doubly Robust
Aggregation Method	Group	Group	Group	Group
Covariates	-	Dependency Ratio	GDP per capita	-
ATT	0.0036	0.0003	0.0038	0.0039
Standard Error	0.0025	0.0022	0.0038	0.0027
Model	**V**	**VI**	**VII**	**VIII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Never Treated	Never Treated	Not Yet Treated	Not Yet Treated
Estimation Method	Regression	Regression	Doubly Robust	Regression
Aggregation Method	Group	Group	Dynamic	Dynamic
Covariates	Dependency Ratio	GDP per capita	-	Dependency Ratio
ATT	0.0020	0.0103**	0.0434**	0.0395**
Standard Error	0.0022	0.0035	0.0138	0.0176
Model	**IX**	**X**	**XI**	**XII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Never Treated	Never Treated	Never Treated
Estimation Method	Regression	Doubly Robust	Regression	Regression
Aggregation Method	Dynamic	Dynamic	Dynamic	Dynamic
Covariates	GDP per capita	-	Dependency Ratio	GDP per capita
ATT	0.0428**	0.0435**	0.0417**	0.0498**
Standard Error	0.0143	0.0175	0.0141	0.0167

Note: The table reports the aggregated group treatment effect (ATT(g,t)) parameters estimated as in Eq. (7) to evaluate the impact of MaPP on NFC GFCF to GDP across groups. The aggregated dynamic treatment effect parameters estimated as in Eq. (9) are also reported to examine the impact of MaPP on NFC GFCF to GDP over time. ATT(g,t) is the average treatment effect experienced by group g in time t. Statistical significance is assessed using clustered bootstrapped standard errors at the country level that also account for the autocorrelation of the data. "**" represents statistical significance at a 5% level and "*" represents statistical significance at a 10% level.

Table 11: Impact of MaPP on Household Savings Rate, Restricted Sample, 2000-2019

Model	I	II	III	IV
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Not Yet Treated	Not Yet Treated	Never Treated
Estimation Method	Doubly Robust	Regression	Regression	Doubly Robust
Aggregation Method	Group	Group	Group	Group
Covariates	-	Dependency Ratio	GDP per capita	-
ATT	0.0204**	0.0274**	0.0238*	0.0196**
Standard Error	0.0058	0.0065	0.0072	0.0063
Model	**V**	**VI**	**VII**	**VIII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Never Treated	Never Treated	Not Yet Treated	Not Yet Treated
Estimation Method	Regression	Regression	Doubly Robust	Regression
Aggregation Method	Group	Group	Dynamic	Dynamic
Covariates	Dependency Ratio	GDP per capita	-	Dependency Ratio
ATT	0.0270**	0.0096	0.0400**	0.0530**
Standard Error	0.0078	0.0068	0.0184	0.0145
Model	**IX**	**X**	**XI**	**XII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Never Treated	Never Treated	Never Treated
Estimation Method	Regression	Doubly Robust	Regression	Regression
Aggregation Method	Dynamic	Dynamic	Dynamic	Dynamic
Covariates	GDP per capita	-	Dependency Ratio	GDP per capita
ATT	0.0313**	0.0389**	0.0510**	0.0106
Standard Error	0.0160	0.0183	0.0152	0.0198

Note: The table reports the aggregated group treatment effect (ATT(g,t)) parameters estimated as in Eq. (7) to evaluate the impact of MaPP on savings across groups. The aggregated dynamic treatment effect parameters estimated as in Eq. (9) are also reported to examine the impact of MaPP on savings over time. ATT(g,t) is the average treatment effect experienced by group g in time t. Statistical significance is assessed using clustered bootstrapped standard errors at the country level that also account for the autocorrelation of the data. "**" represents statistical significance at a 5% level and "*" represents statistical significance at a 10% level.

Table 12: Impact of MaPP on Firm Investment Rate, Restricted Sample, 2000-2019

Model	**I**	**II**	**III**	**IV**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Not Yet Treated	Not Yet Treated	Never Treated
Estimation Method	Doubly Robust	Regression	Regression	Doubly Robust
Aggregation Method	Group	Group	Group	Group
Covariates	-	Dependency Ratio	GDP per capita	-
ATT	0.0112**	0.0091**	0.0062*	0.0096**
Standard Error	0.0026	0.0032	0.0032	0.0015
Model	**V**	**VI**	**VII**	**VIII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Never Treated	Never Treated	Not Yet Treated	Not Yet Treated
Estimation Method	Regression	Regression	Doubly Robust	Regression
Aggregation Method	Group	Group	Dynamic	Dynamic
Covariates	Dependency Ratio	GDP per capita	-	Dependency Ratio
ATT	0.0089**	0.0114*	0.0822**	0.0770**
Standard Error	0.0021	0.0037	0.0237	0.0196
Model	**IX**	**X**	**XI**	**XII**
Period	2000-2019	2000-2019	2000-2019	2000-2019
Treatment Group	Not Yet Treated	Never Treated	Never Treated	Never Treated
Estimation Method	Regression	Doubly Robust	Regression	Regression
Aggregation Method	Dynamic	Dynamic	Dynamic	Dynamic
Covariates	GDP per capita	-	Dependency Ratio	GDP per capita
ATT	0.0678**	0.0776**	0.0748**	0.0793**
Standard Error	0.0251	0.0237	0.0216	0.0257

Note: The table reports the aggregated group treatment effect (ATT(g,t)) parameters estimated as in Eq. (7) to evaluate the impact of MaPP on investment across groups. The aggregated dynamic treatment effect parameters estimated as in Eq. (9) are also reported to examine the impact of MaPP on savings over time. ATT(g,t) is the average treatment effect experienced by group g in time t. Statistical significance is assessed using clustered bootstrapped standard errors at the country level that also account for the autocorrelation of the data. "**" represents statistical significance at a 5% level and "*" represents statistical significance at a 10% level.

Appendices

A Data

Variable	Type	Source	Details
Dependency Ratio	Control	Eurostat	Ratio between the number of persons aged 65 and over (age when they are generally economically inactive) and the number of persons aged between 15 and 64. This indicator is published annually, and it was assumed constant for all quarters within the year.
DSTI ratio	Policy	IMF iMaPP	Limits to the debt-service-to-income ratio and the loan-to-income ratio, which restrict the size of debt services or debt relative to income. They include those targeted at housing loans, consumer loans, and commercial real estate loans. Index cumulated to a quarterly frequency.
Firm Investment Rate	Dependent	Eurostat	Gross fixed capital formation (P51) divided by gross value added (B1G) of NFC. Seasonally and calendar adjusted. Quarterly data.
GDP per capita	Control	Eurostat	Gross domestic product at market prices. Million euros. Seasonally and calendar adjusted. Divided by total population. Total population is published annually, and it was assumed constant for all quarters within the year. Quarterly data.
HH Consumption to GDP	Dependent	Eurostat	Private consumption expenditure consists of expenditure incurred for the direct satisfaction of individual or collective needs by private households or non-profit institutions serving households. Seasonally and calendar adjusted. Quarterly data.
HH Loan Restrictions	Policy	IMF iMaPP	Household loan restrictions include mainly loan limits and may be conditioned on loan characteristics like the maturity, the size, the type of interest rate and the LTV ratio. Index cumulated to a quarterly frequency.
Household (HH) Savings Rate	Dependent	Eurostat	Gross saving (B8G) divided by gross disposable income adjusted for changes in pension entitlements (B6G + D8net); Seasonally and calendar adjusted. Quarterly data.
LTV ratio	Policy	IMF iMaPP	Limits to the loan-to-value ratios, including those mostly targeted at housing loans, but also those targeted at automobile loans, and commercial real estate loans. Index cumulated to a quarterly frequency.
NFC GFCF to GDP	Dependent	Eurostat	GFCF consists of resident producers' acquisitions, less disposals of fixed assets plus certain additions to the value of non-produced assets realised by productive activity, such as improvements to land. Seasonally and calendar adjusted. Quarterly data.
NFC Loan Restrictions	Policy	IMF iMaPP	Firm loan restrictions include mainly loan limits and may be conditioned on loan characteristics like the maturity, the size, the type of interest rate and the LTV ratio. Index cumulated to a quarterly frequency.

B Summary Statistics

Sample	Obs.	Mean	Std. Dev	Min	Max
HH Savings Rate: Full Sample					
HH Savings Rate	1200	0.11	0.04	0.00	0.20
Dependency Ratio	1200	0.26	0.04	0.15	0.36
GDP per capita	1200	7.34	3.11	1.17	18.58
Firm Investment Rate: Full Sample					
Firm Investment Rate	1200	0.24	0.06	0.09	1.25
Dependency Ratio	1200	0.26	0.04	0.15	0.36
GDP per capita	1200	7.37	3.07	1.05	18.58
HH Savings Rate: Control Group (Full)					
HH Savings Rate	760	0.12	0.04	0.00	0.20
Dependency Ratio	760	0.26	0.04	0.18	0.36
GDP per capita	760	6.49	2.53	1.17	11.23
HH Savings Rate: Not Yet Treated Countries					
HH Savings Rate	360	0.09	0.03	0.00	0.18
Dependency Ratio	360	0.24	0.03	0.18	0.34
GDP per capita	360	4.94	2.66	1.17	9.32
Firm Investment Rate: Control Group (Full)					
Firm Investment Rate	818	0.24	0.05	0.12	0.41
Dependency Ratio	818	0.26	0.04	0.18	0.36
GDP per capita	818	6.51	2.54	1.05	11.23
Firm Investment Rate: Not Yet Treated Countries					
Firm Investment Rate	418	0.26	0.05	0.12	0.41
Dependency Ratio	418	0.25	0.04	0.18	0.34
GDP per capita	418	5.03	2.56	1.05	9.24

Note: The table reports summary statistics of pre-treatment variables for control and treatment groups. The full control group includes never treated and not yet treated countries. The statistics are further disaggregated into a subset of not yet countries that adopt MaPP during the sample period.

C Unit Root Tests

Maddala and Wu (1999) test	Obs.	Statistic	P-Value
HH Savings Rate	1200	193.751	0.000
HH Consumption to GDP	1600	129.887	0.000
Firm Investment Rate	1200	236.652	0.000
NFC GFCF to GDP	1280	212.983	0.000
Dependency Ratio	1600	26.644	0.948
GDP per capita	1600	9.896	0.000

Pesaran (2007) test	Obs.	Statistic	P-Value
HH Savings Rate	1200	-6.821	0.000
HH Consumption to GDP	1600	-7.454	0.000
Firm Investment Rate	1200	-8.984	0.000
NFC GFCF to GDP	1280	-8.542	0.000
Dependency Ratio	1600	-0.502	0.308
GDP per capita	1600	-2.335	0.000

Note: The table presents the First generation Maddala and Wu (1999) test and second generation Pesaran (2007) test for panel unit roots results based on H_0: All panels contain unit roots and H_a: At least one panel is stationary. The results of an Inverse Chi-squared test are presented above with both the test statistic and the p-value being displayed. The presence of a unit root is always rejected because the p-value is less than 0.1 except for the case of the dependency ratio.

D Cramer-von-Mises Tests

	HH Savings Rate		
Covariates	-	Dependency Ratio	GDP per capita
CvM Test Statistic	0.0673	0.0451	0.0560
CvM Critical Value	0.3253	0.3501	0.4912
CvM P-Value	0.8400	0.9760	0.9210

	Firm Investment Rate		
Covariates	-	Dependency Ratio	GDP per capita
CvM Test Statistic	0.1372	0.1397	0.1586
CvM Critical Value	0.4527	0.7462	1.0857
CvM P-Value	0.8190	0.9640	0.9460

Note: The tables present the CvM test for the presence of (un)conditional parallel pre-trends based on H_0: (Un)conditional parallel pre-trends hold and H_a: (Un)conditional parallel pre-trends do not hold. The results of the Wald-type test are presented in the above table with both the test statistic and the p-value being displayed. Note that we always fail to reject the presence of parallel trends as the p-value is greater than 0.10.

E Control and Treated Groups

Variable	Treated Group	"Never" Treated Control Group
HH Savings Rate	Czech Republic	Austria
	Denmark	Belgium
	Finland	France
	Ireland	Germany
	Netherlands	Italy
	Poland	
	Portugal	
	Sweden	
	United Kingdom	
HH Consumption to GDP	Croatia	Austria
	Czech Republic	Belgium
	Denmark	France
	Estonia	Germany
	Finland	Italy
	Hungary	
	Latvia	
	Netherlands	
	Poland	
	Portugal	
	Slovakia	
	Slovenia	
	Sweden	
	United Kingdom	
Firm Investment Rate	Czech Republic	Austria
	Denmark	Belgium
	Estonia	Germany
	Finland	Italy
	France	United Kingdom
	Netherlands	
	Poland	
	Portugal	
	Sweden	
NFC GFCF to GDP	Czech Republic	Austria
	Denmark	Belgium
	Estonia	Germany
	Finland	Italy
	France	United Kingdom
	Hungary	
	Netherlands	
	Poland	
	Portugal	
	Sweden	

Note: List of countries in the control and treated groups for the DiD estimations on household consumption and firm investment. A country is assigned to the treatment group if it implements MaPP at some point in time in the sample period. A country is assigned to the "never treated" control group if it "never" implements MaPP in the sample period. An important point to note is that the control group in our main models will also include countries that have "not yet" implemented MaPP at the time of implementation of MaPP for every group g.

F MaPP Adoption

Country	Date of implementation	Policy Implemented
Croatia	2006-Q4	LTV
Czech Republic	2015-Q2	LTV, Household Loan Restrictions
Denmark	2003-Q2	Household Loan Restrictions, NFC Loan Restrictions
Estonia	2015-Q1	LTV, Household Loan Restrictions, DSTI
Finland	2010-Q1	LTV
France	2018-Q3	NFC Loan Restrictions
Hungary	2010-Q1	LTV, Household Loan Restrictions, DSTI
Ireland	2001-Q4	LTV
Latvia	2007-Q1	NFC Loan Restrictions
Netherlands	2007-Q1	DSTI
Poland	2006-Q4	Household Loan Restrictions
Portugal	2018-Q3	LTV, Household Loan Restrictions, DSTI
Slovakia	2014-Q4	LTV
Slovenia	2016-Q3	LTV, DSTI
Sweden	2004-Q3	LTV
United Kingdom	2009-Q1	Household Loan Restrictions

Note: Date of first implementation of MaPP for every country in our sample and brief description of the policy.

References

[1] Acharya, VV., Bergant, K., Crosignani, M., Eisert, T. and McCann, F. (2020), “The Anatomy of the Transmission of Macroprudential Policies”, *IMF Working Paper* WP/20/58.

[2] Akinci, O. and Olmstead-Rumsey, J. (2018), “How effective are macroprudential policies? An empirical investigation”, *Journal of Financial Intermediation* 33(C): 33-57.

[3] Alam, Z., Alter, A., Eiseman, J., Gelos, G., Kang, H., Narita, M., Nier, E. and Wang, N. (2019), “Digging Deeper - Evidence on the Effects of Macroprudential Policies from a New Database”, *IMF Working Paper* WP/19/66.

[4] Angelini, P., Neri, S. and Panetta, F. (2014), “The Interaction between Capital Requirements and Monetary Policy”, *Journal of Money, Credit and Banking* 46(6): 1073-1112.

[5] Behncke, S. (2020), ”Effects of macroprudential policies on bank lending and credit risks”, *Swiss National Bank Working Papers* 2020-06.

[6] Borio, C. and Shim, I. (2007), “What can (macro-)prudential policy do to support monetary policy?”, *BIS Working Papers* 242, Bank for International Settlements.

[7] Callaway, B. and Sant’Anna, PHC. (2020), “Difference-in-Differences with multiple time periods”, *Journal of Econometrics*.

[8] Carroll, CD., Slacalek, J. and Sommer, M. (2019), “Dissecting Saving Dynamics: Measuring Wealth, Precautionary and Credit Effects”, *NBER Working Paper Series* No. 26131.

[9] Cerutti, E., Claessens, S. and Laeven, L. (2017), “The use and effectiveness of macroprudential policies: new evidence”, *Journal of Financial Stability* 28: 203-24.

[10] Claessens, S., Ghosh, SR, Mihet, R. (2013), “Macro-prudential policies to mitigate financial system vulnerabilities”, *Journal of International Money and Finance* 39: 153-85.

[11] Crowe, CW., Igan, D., Dell’Ariccia, G and Rabanal, P. (2011), “How to Deal with Real Estate Booms”, *IMF Staff Discussion Note* 11/02.

[12] Defusco, AA., Johnson, S. and Mondragon, J. (2020), “Regulating Household Leverage”, *The Review of Economic Studies* 87(2): 914-958.

[13] Delll’Ariccia, G., Igan, D., Laeven, L. and Tong, H. (2012), “Policies for Macrofinancial Stability: How to Deal with Credit Booms”, *IMF Staff Discussion Note* 12/06.

[14] Eggertsson, G. and Krugman, P. (2012), Debt, “Deleveraging, and the Liquidity Trap: A Fisher-Minsky-Koo Approach”, *The Quarterly Journal of Economics*.

[15] Farhi, E. and Werning, I. (2016), “A Theory of Macroprudential Policies in the Presence of Nominal Rigidities”, *Econometrica* 84 (5): 1645-1704.

[16] Galac, T. and Kraft, E. (2007), “Macroprudential Regulation of Credit Booms and Busts – the Case of Croatia”, *World Bank Policy Research Working Paper* No. 5772, Available at SSRN: https://ssrn.com/abstract=1914983.

[17] Guerrieri, V. and Lorenzoni, G. (2017), "Credit Crises, Precautionary Savings, and the Liquidity Trap", *The Quarterly Journal of Economics* 132(3): 1427-1467.

[18] Hall, RE. (2011), "The Long Slump", *American Economic Review* 101 (2): 431-69.

[19] Kuttner, KN. and Shim, I. (2013), "Can non-interest rate policies stabilise housing markets? Evidence from a panel of 57 economies", *BIS Working Papers* 433 (November).

[20] Lim, C., Columba, F., Costa, A., Kongsamut, P., Otani, A., Saiyid, M., Wezel, T. and Wu, X. (2011), "Macroprudential Policy: What Instruments and How to Use Them? Lessons from Country Experiences", *IMF Working Paper* 11/238.

[21] Maddala, GS. and Wu, S. (1999), "A Comparative Study of Unit Root Tests with Panel Data and a New Simple Test", *Oxford Bulletin of Economics and Statistics* 61: 631-652.

[22] Mody, A., Ohnsorge, F. and Sandri, D. (2012), "Precautionary Savings in the Great Recession", *IMF Economic Review* 60(1): 114-138.

[23] Pesaran, MH. (2007), "A simple panel unit root test in the presence of cross-section dependence", *Journal of Applied Econometrics* 22(2): 265-312.

[24] Richter, B., Schularick, M. and Shim, I. (2019), "The Costs of Macroprudential Policy", *Journal of International Economics* 118:263-282.

[25] Sun, Z. and Wang, Y. (2015), "Corporate precautionary savings: Evidence from the recent financial crisis", *The Quarterly Review of Economics and Finance* 56(C): 175-186.