

Macroprudential Policy and Aggregate Demand*

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This paper assesses the impact of macroprudential policy (MaPP) on aggregate demand in the EU between 2000 and 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.

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, Claessens, and Laeven 2017). Not surprisingly, these studies find an inverse relationship between the adoption of MaPP and economic growth. Their story

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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 imperils growth. Relative to these papers, we directly link the adoption of MaPP to movements 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.

Third, we distinguish between the short- and long-run effects of MaPP. Separating out the two is an empirically difficult matter, but we are able to 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.

As we shall see, our results indicate that MaPP has asymmetric effects on consumption and investment. In particular, we find that 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. Furthermore, 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, Ghosh, and Mihet 2013). Moreover, MaPP lessens the probability of a crisis (e.g., Galac and Kraft 2011), especially in housing markets (Crowe et al. 2011; Kuttner and Shim 2013). This 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, Angelini, Neri, and Panetta (2014) 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 relationship 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; Guierriero and Lorenzoni 2017).

This theoretical work finds empirical support in studies that use regressions and time-series models to estimate the effects of MaPP on growth (e.g., Lim et al. 2011; Cerutti, Claessens, and Laeven 2017; Akinci and Olmstead-Rumsey 2018). This stream of research amassed a remarkable body of evidence on a negative relationship between MaPP and output growth. These studies generally conclude that MaPP should be tightened in boom periods and loosened in bust periods. Yet, they offer little explanation on the transmission channels of MaPP, i.e., the way in which MaPP is supposed to have affected output. This 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, Johnson, and Mondragon (2020) use a DiD strategy to exploit a policy-induced discontinuity in the debt-service-to-income ratio in the United States. 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 perhaps 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 (2021). 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 $t = 1, \dots, \tau$ and D_t is a binary variable that equals 1 when a country implements MaPP 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:

$$Y_t = D_t Y_t(1) + (1 - D_t) Y_t(0), \quad (1)$$

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:

$$ATT(g, t) = E[Y_t(1) - Y_t(0) | G_g = 1]. \quad (2)$$

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 non-parametrically identified and estimated as below:¹

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

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:

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

¹Callaway and Sant’Anna (2021) show that Equation (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 assumption (Appendix C). The second assumption states that a country that adopts MaPP is forever treated, which is consistent with the behavior of countries in our sample that rarely reverse MaPP. The last assumption simply requires a control group for every treatment period.

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:

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

where $k = \sum_{g=2}^{\tau} \sum_{t=2}^{\tau} \mathbf{1}\{g \leq t\} P(G = g)$ 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:

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

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

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:

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

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 over longer horizons when households and firms have had the time to adjust their behavior. 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:

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

where e is the length of exposure to MaPP.

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 two quarters. The $ATT(g, t)$ is computed iteratively in this way for $e = 0, \dots, 40$.

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

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

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 are readily available from Eurostat. To provide robustness checks, we also consider other proxies like household consumption to GDP and non-financial corporations (NFCs) gross fixed capital formation (GFCF) to GDP. Summary statistics are presented in Table 1.

We assign to the treated group every country that implements prudential rules to reduce banks' exposure to household and firm

³Our initial data set comprises the 27 member states of the European Union 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 are missing in the pre-treatment or post-treatment periods.

Table 1. Summary Statistics

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

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 treated countries that have not yet adopted MaPP during the sample period.

risks. This includes the loan-to-value (LTV) ratio, debt-service-to-income (DSTI) ratio, and loan restrictions.⁴ The data were collected from the International Monetary Fund (IMF) iMaPP database (Alam et al. 2019) and updated with information from the European Central Bank’s 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 *Baseline Results*

Table 2 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 surprisingly consistent across models, ranging from 1.87 to 2.41 percentage points. To be clear, this estimate for savings is not a small number. The average savings rate in our sample is only 11.33 percent,

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

⁵Other 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. In any case, GDP per capita should partially capture these effects.

Table 2. Impact of MaPP on Household Savings Rate, 2000–19

| Model | (1) | (2) | (3) | (4) |
|---|------------------|------------------|------------------|------------------|
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| Treatment Group | Not Yet Treated | Not Yet Treated | Not Yet Treated | Not Yet 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 | (5) | (6) | (7) | (8) |
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 | (9) | (10) | (11) | (12) |
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 |
| <p>Note: The table reports the aggregated group treatment effect ($ATT(g, t)$) parameters estimated as in Equation (7) to evaluate the impact of MaPP on savings across groups. The aggregated dynamic treatment effect parameters estimated as in Equation (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 percent level and * represents statistical significance at a 10 percent level.</p> | | | | |

which means that MaPP pushes savings up by approximately one quarter.

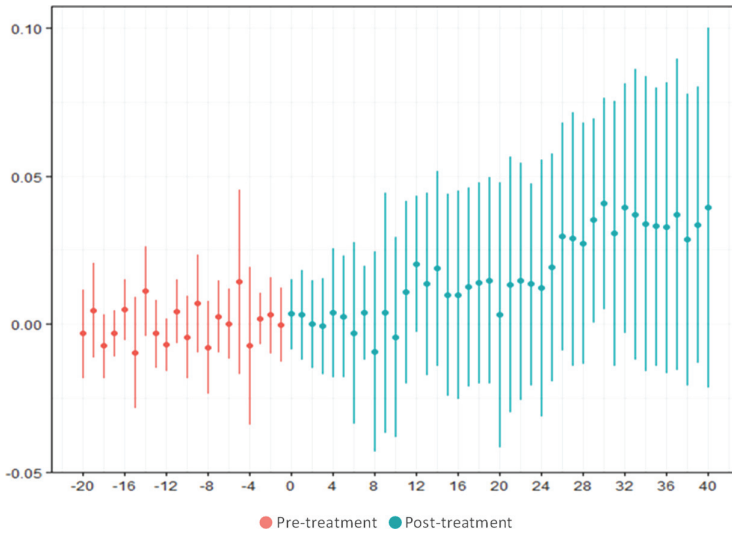
The vast majority of group-time treatment effects are statistically significant, and they stand up to robustness checks that control for demographics and income. They also hold when we restrict the control group to “never treated” countries. When we control for demography and income, the group-time treatment 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. These 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 to 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 3.

The uncanny finding that MaPP has a lower impact in the short run is not entirely new. A couple of papers using regressions to estimate the effects of MaPP over a four-year window report a severe contraction in credit and output around year 3 (e.g., Borio and Shim 2007; Richter, Schularick, and Shim 2019). Our estimates now provide a potential explanation for the plunging output: households reduce their consumption and increase savings around year 3.

Table 3 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.

Figure 1. Dynamic Impact of MaPP on Household Savings Rate, Full Sample, 2000–19



Note: The red dots are the pre-treatment pseudo group-time average treatment effects, which are plotted to pre-test the parallel trends assumption. The blue dots are the post-treatment group-time average treatment effects, which measure the average effect of adopting MaPP in quarter n th for all groups that implement MaPP in that quarter. The x-axis is the length of exposure to MaPP. A length of exposure equal to 0 corresponds to the average effect of implementing MaPP across groups in the first quarter after the adoption of MaPP; equal to -1 corresponds to the quarter before groups implement MaPP; and equal to 1 corresponds to the first quarter after initial adoption.

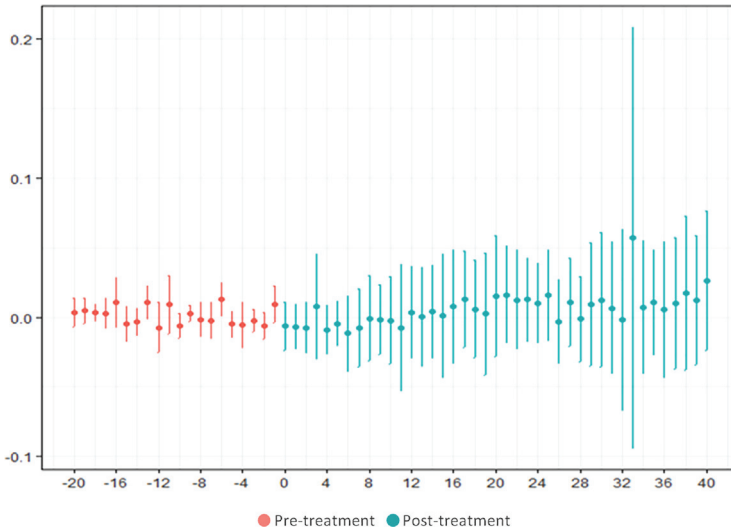
Not surprisingly, the results for the dynamic effects on investment are far more enlightening. Our estimates show that MaPP increases firm investment by 5.05–6.63 percentage points over time. This corresponds to an increase of more than one quarter in firm investment, since the average investment rate in our sample is 23.94 percent. 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 4, 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.

Table 3. Impact of MaPP on Firm Investment Rate, 2000–19

| Model | (1) | (2) | (3) | (4) |
|--------------------|------------------|------------------|------------------|------------------|
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 | (5) | (6) | (7) | (8) |
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 | (9) | (10) | (11) | (12) |
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 Equation (7) to evaluate the impact of MaPP on investment across groups. The aggregated dynamic treatment effect parameters estimated as in Equation (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 percent level and * represents statistical significance at a 10 percent level.

Figure 2. Dynamic Impact of MaPP on Firm Investment Rate, Full Sample, 2000–19



Note: The red dots are the pre-treatment pseudo group-time average treatment effects, which are plotted to pre-test the parallel trends assumption. The blue dots are the post-treatment group-time average treatment effects, which measure the average effect of adopting MaPP in quarter n th for all groups that implement MaPP in that quarter. The x-axis is the length of exposure to MaPP. A length of exposure equal to 0 corresponds to the average effect of implementing MaPP across groups in the first quarter after the adoption of MaPP; equal to -1 corresponds to the quarter before groups implement MaPP; and equal to 1 corresponds to the first quarter after initial adoption.

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 4–9 provide the estimations of the impact of LTV ratios, loan restrictions, and DSTI ratios on household savings and firm investment. In Tables 4 and 7, 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. Still, the impact remains positive, which is consistent with our main findings.

Tables 5 and 8 provide the estimates for the impact of loan restrictions on savings and investment, respectively. In short, 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, Claessens, and Laeven 2017).

Tables 6 and 9 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 meager. The DSTI ratio, then, has a greater impact on consumption than on investment.

Table 4. Impact of MaPP on Household Savings Rate, LTV, 2000–19

| Model | (1) | (2) | (3) | (4) |
|--------------------|------------------|------------------|------------------|------------------|
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| Treatment Group | Not Yet Treated | Not Yet Treated | Not Yet Treated | Not Yet 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 | (5) | (6) | (7) | (8) |
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 | (9) | (10) | (11) | (12) |
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 Equation (7) to evaluate the impact of MaPP on savings across groups. The aggregated dynamic treatment effect parameters estimated as in Equation (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 percent level and * represents statistical significance at a 10 percent level.

Table 5. Impact of MaPP on Household Savings Rate, Loan Restrictions, 2000–19

| Model | (1) | (2) | (3) | (4) |
|--------------------|------------------|------------------|------------------|------------------|
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 | (5) | (6) | (7) | (8) |
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 | (9) | (10) | (11) | (12) |
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 Equation (7) to evaluate the impact of MaPP on savings across groups. The aggregated dynamic treatment effect parameters estimated as in Equation (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 percent level and * represents statistical significance at a 10 percent level.

Table 6. Impact of MaPP on Household Savings Rate, DSTI, 2000–19

| Model | (1) | (2) | (3) | (4) |
|--------------------|------------------|------------------|------------------|------------------|
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| Treatment Group | Not Yet Treated | Not Yet Treated | Not Yet Treated | Not Yet 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 | (5) | (6) | (7) | (8) |
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 | (9) | (10) | (11) | (12) |
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 Equation (7) to evaluate the impact of MaPP on savings across groups. The aggregated dynamic treatment effect parameters estimated as in Equation (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 percent level and * represents statistical significance at a 10 percent level.

Table 7. Impact of MaPP on Firm Investment Rate, LTV, 2000–19

| Model | (1) | (2) | (3) | (4) |
|--------------------|------------------|------------------|------------------|------------------|
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 | (5) | (6) | (7) | (8) |
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 | (9) | (10) | (11) | (12) |
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 Equation (7) to evaluate the impact of MaPP on investment across groups. The aggregated dynamic treatment effect parameters estimated as in Equation (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 percent level and * represents statistical significance at a 10 percent level.

Table 8. Impact of MaPP on Firm Investment Rate, Loan Restrictions, 2000–19

| Model | (1) | (2) | (3) | (4) |
|--------------------|------------------|------------------|------------------|------------------|
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| Treatment Group | Not Yet Treated | Not Yet Treated | Not Yet Treated | Not Yet 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 | (5) | (6) | (7) | (8) |
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 | (9) | (10) | (11) | (12) |
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 Equation (7) to evaluate the impact of MaPP on investment across groups. The aggregated dynamic treatment effect parameters estimated as in Equation (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 percent level and * represents statistical significance at a 10 percent level.

Table 9. Impact of MaPP on Firm Investment Rate, DSTI, 2000–19

| Model | (1) | (2) | (3) | (4) |
|--------------------|------------------|------------------|------------------|------------------|
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 | (5) | (6) | (7) | (8) |
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 | (9) | (10) | (11) | (12) |
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 Equation (7) to evaluate the impact of MaPP on investment across groups. The aggregated dynamic treatment effect parameters estimated as in Equation (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 percent level and * represents statistical significance at a 10 percent level.

Our bottom-line result is that measures that directly restrict access to credit—mainly the LTV and the DSTI ratio—have a stronger impact on the spending components of aggregate demand. But it is worth noting that their impact is 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 10 and 11 provide the estimations of the DiD using these alternative proxies. We find that household consumption is 0.67 percentage point 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.

Table 10. Impact of MaPP on Household Consumption to GDP, 2000–19

| Model | (1) | (2) | (3) | (4) |
|--------------------|------------------|------------------|------------------|------------------|
| Treatment Group | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| Estimation Method | Not Yet Treated | Not Yet Treated | Not Yet Treated | Never Treated |
| Aggregation Method | Doubly Robust | Regression | Regression | Doubly Robust |
| Covariates | Group | Group | Group | Group |
| ATT | — | Dependency Ratio | GDP per Capita | — |
| Standard Error | -0.0067* | -0.0084** | -0.0104** | -0.0050 |
| | 0.0036 | 0.0033 | 0.0037 | 0.0033 |
| Model | (5) | (6) | (7) | (8) |
| Treatment Group | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| Estimation Method | Never Treated | Never Treated | Not Yet Treated | Not Yet Treated |
| Aggregation Method | Regression | Regression | Doubly Robust | Regression |
| Covariates | Group | Group | Dynamic | Dynamic |
| ATT | Dependency Ratio | GDP per Capita | — | Dependency Ratio |
| Standard Error | -0.0053* | -0.0037 | -0.0247** | -0.0283** |
| | 0.0030 | 0.0069 | 0.0108 | 0.0117 |
| Model | (9) | (10) | (11) | (12) |
| Treatment Group | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| Estimation Method | Not Yet Treated | Never Treated | Never Treated | Never Treated |
| Aggregation Method | Regression | Doubly Robust | Regression | Regression |
| Covariates | Dynamic | Dynamic | Dynamic | Dynamic |
| ATT | GDP per Capita | — | Dependency Ratio | GDP per Capita |
| Standard Error | -0.0156 | -0.0220** | -0.0232** | -0.0037 |
| | 0.0137 | 0.0109 | 0.0110 | 0.0169 |

Note: The table reports the aggregated group treatment effect ($ATT(g, t)$) parameters estimated as in Equation (7) to evaluate the impact of MaPP on consumption to GDP across groups. The aggregated dynamic treatment effect parameters estimated as in Equation (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 percent level and * represents statistical significance at a 10 percent level.

Table 11. Impact of MaPP on NFC GFCF to GDP, 2000–19

| Model | (1) | (2) | (3) | (4) |
|--------------------|------------------|------------------|------------------|------------------|
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| Treatment Group | Not Yet Treated | Not Yet Treated | Not Yet Treated | Not Yet 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 | (5) | (6) | (7) | (8) |
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 | (9) | (10) | (11) | (12) |
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 Equation (7) to evaluate the impact of MaPP on NFC GFCF to GDP across groups. The aggregated dynamic treatment effect parameters estimated as in Equation (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 percent level and * represents statistical significance at a 10 percent level.

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 12 and 13 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 and 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.

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

⁶Only Denmark, the Netherlands, and Poland remove or loosen a prudential rule during our sample period. These countries are excluded from this restricted sample.

Table 12. Impact of MaPP on Household Savings Rate, Restricted Sample, 2000–19

| Model | (1) | (2) | (3) | (4) |
|--------------------|------------------|------------------|------------------|------------------|
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| Treatment Group | Not Yet Treated | Not Yet Treated | Not Yet Treated | Not Yet 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 | (5) | (6) | (7) | (8) |
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 | (9) | (10) | (11) | (12) |
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 |

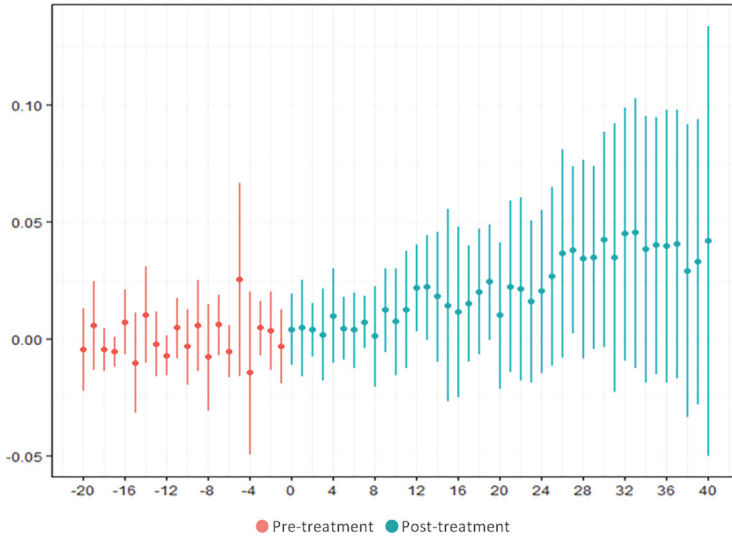
Note: The table reports the aggregated group treatment effect ($ATT(g, t)$) parameters estimated as in Equation (7) to evaluate the impact of MaPP on savings across groups. The aggregated dynamic treatment effect parameters estimated as in Equation (9) are also reported to examine the impact of MaPP 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 percent level and * represents statistical significance at a 10 percent level.

Table 13. Impact of MaPP on Firm Investment Rate, Restricted Sample 2000–19

| Model | (1) | (2) | (3) | (4) |
|--------------------|------------------|------------------|------------------|------------------|
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 | (5) | (6) | (7) | (8) |
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 | (9) | (10) | (11) | (12) |
| Period | 2000–19 | 2000–19 | 2000–19 | 2000–19 |
| 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 Equation (7) to evaluate the impact of MaPP on investment across groups. The aggregated dynamic treatment effect parameters estimated as in Equation (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 percent level and * represents statistical significance at a 10 percent level.

Figure 3. Dynamic Impact of MaPP on Household Savings Rate, Restricted Sample, 2000–19



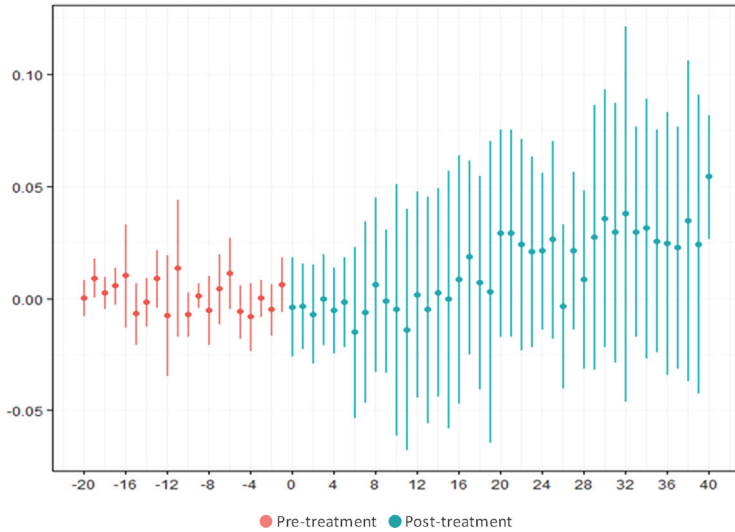
Note: The red dots are the pre-treatment pseudo group-time average treatment effects, which are plotted to pre-test the parallel trends assumption. The blue dots are the post-treatment group-time average treatment effects, which measure the average effect of adopting MaPP in quarter n th for all groups that implement MaPP in that quarter. The x-axis is the length of exposure to MaPP. A length of exposure equal to 0 corresponds to the average effect of implementing MaPP across groups in the first quarter after the adoption of MaPP; equal to -1 corresponds to the quarter before groups implement MaPP; and equal to 1 corresponds to the first quarter after initial adoption.

dynamic effects in Figure 4, we can see that GFCF starts to rise significantly after year 4, which is also in line with the pattern of the firm investment rate. This is reassuring despite 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

Figure 4. Dynamic Impact of MaPP on Firm Investment Rate, Restricted Sample, 2000–19



Note: The red dots are the pre-treatment pseudo group-time average treatment effects, which are plotted to pre-test the parallel trends assumption. The blue dots are the post-treatment group-time average treatment effects, which measure the average effect of adopting MaPP in quarter n th for all groups that implement MaPP in that quarter. The x-axis is the length of exposure to MaPP. A length of exposure equal to 0 corresponds to the average effect of implementing MaPP across groups in the first quarter after the adoption of MaPP; equal to -1 corresponds to the quarter before groups implement MaPP; and equal to 1 corresponds to the first quarter after initial adoption.

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 LTV and DSTI ratios have a deleterious impact on household consumption even though the LTV ratio has a positive effect on firm investment. A potential explanation for this result 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 MaPP. An unintended consequence is that we cannot fully capture the effects of loosening, tightening, or removing MaPP. We address this caveat by rerunning our model on a restricted sample of countries that never loosen or remove MaPP. But it would also be interesting to assess how changes in the overall macroprudential stance affect consumption and investment.

Second, the staggered DiD cannot completely disentangle the effects of MaPP from other country-specific macroeconomic events. This is because MaPP is usually adopted in response to contemporaneous events. That said, our aggregation of average treatment effects into a single causal parameter reduces estimation uncertainty. Furthermore, our results are robust to a number of different dependent variables, samples, and controls. Future work could investigate how the interaction of MaPP with other policies influences aggregate demand.

Lastly, our results provide suggestive evidence that some MaPP tools have a disproportionately 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. Instead, our results support the view that policymakers should continuously adjust MaPP in much the same way as monetary policy. But given that MaPP has the ability to drive spending, policymakers should be cautious about using it liberally.

Appendix A. Data Sources and Details

Table A.1. Data Sources and Details

| Variable | Type | Source | Details |
|-----------------------------|-----------|-----------|---|
| 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 realized by productive activity, such as improvements to land. Seasonally and calendar adjusted. Quarterly data. |
| Firm Investment Rate | Dependent | Eurostat | Gross fixed capital formation (P51) divided by gross value-added (BIG) of NFC. Seasonally and calendar adjusted. Quarterly data. |
| 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. |
| 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. |
| 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. |
| GDP per Capita | Control | ECB MPDB | 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 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. |
| 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. |
| 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. |
| 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. |

Appendix B. Unit-Root Tests

Table B.1. Unit-Root Tests

| | Observations | Statistic | P-Value |
|--|--------------|-----------|---------|
| Maddala and Wu (1999) Test | | | |
| 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 |
| HH GDP per Capita | 1600 | 9.896 | 0.000 |
| Pesaran (2007) Test | | | |
| 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 |
| HH GDP per Capita | 1600 | -2.335 | 0.000 |
| <p>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.</p> | | | |

Appendix C. Cramer-von-Mises Tests

Table C.1. Cramer-von-Mises Tests

| Covariates | HH Savings Rate | | |
|--------------------|----------------------|------------------|----------------|
| | No 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 |
| Covariates | Firm Investment Rate | | |
| | No 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 table presents 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 above 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.

Appendix D. Control and Treated Groups in the DiD

Table D.1. Control and Treated Groups in the DiD

| Variable | Treated Group | “Never” Treated Control Group |
|-----------------|---|--|
| HH Savings Rate | Czech Republic Denmark Finland Hungary Ireland The Netherlands Poland Portugal Sweden United Kingdom | Austria Belgium France Germany Italy |

(continued)

Table D.1. (Continued)

| Variable | Treated Group | “Never” Treated Control Group |
|--|--|--|
| HH Consumption to GDP | Croatia Czech Republic Denmark Estonia Finland Hungary Latvia The Netherlands Poland Portugal Slovakia Slovenia Sweden United Kingdom | Austria Belgium France Germany Italy |
| Firm Investment Rate | Czech Republic Denmark Estonia Finland France The Netherlands Poland Portugal Sweden | Austria Belgium Germany Italy United Kingdom |
| NFC GFCF to GDP | Czech Republic Denmark Estonia Finland France Hungary The Netherlands Poland Portugal Sweden | Austria Belgium Germany Italy United Kingdom |
| <p>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.</p> | | |

Appendix E. MaPP Adoption

Table E.1. 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.

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