DNB Working Paper

No. 598 / May 2018

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DeNederlandscheBank

EUROSYSTEEM

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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

Working Paper No. 598

May 2018

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Macroprudential policy and income inequality*

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28 May 2018

Abstract

Based on newly available data, we examine the relationship between macroprudential policies (MaPs) and the Gini coefficient of both market income inequality, i.e. the Gini coefficient of income inequality before redistributive policies, and net income inequality, i.e. inequality after redistribution. We run panel regressions for 69 countries over the period 2000 to 2013. Our results show a positive association of the use of some MaPs with both market and net income inequality. In particular, we find that concentration limits, macroprudential reserve requirements and interbank exposure limits have a positive relationship with market income inequality, while loan-to-value (LTV) limits have a positive association with net inequality. The results for other measures are relatively sensitive to specification.

Keywords: macroprudential policy, financial regulation, inequality, income distribution.
JEL classifications: D63, F38, G28, O16.

* For helpful comments, the authors would like to thank Patty Duijm, Peter Wierts, Robert Vermeulen, Cees Ullersma, Pierre Monnin, Gregory Thwaites, Stijn Claessens and participants at the CEP-IMF Seminar on Monetary Policy, Macroprudential Policy and Inequality (Zurich, 3-4 October 2016), an IMF Jobs and Growth Seminar (21 November 2016), a UW International Economics and Macroeconomics Seminar (29 November 2016) and two anonymous referees. We thank Khuong Vu for sharing data with us. The views are those of the authors and do not necessarily reflect those of De Nederlandsche Bank or the Financial Stability Board. The final version of this paper has been published as Jon Frost and René van Stralen (2018), "Macroprudential policy and income inequality," *Journal of International Money and Finance*, 85(C): 278-290.

1. Introduction

The global financial crisis has spawned a wide range of economic changes. Output in most advanced economies has suffered a major shock, and in many cases has not yet recovered to pre-crisis levels. Unemployment has risen dramatically before falling again in some countries, while remaining intractably high in others. Interest rates in many countries are at their lowest level in recorded history. Income inequality, which had increased in many advanced economies since the 1970's, has continued to rise (Piketty, 2014; Atkinson, 2014). Finally, the financial sector has been subjected to a raft of new regulations meant to stave off future crises. As a policy area, macroprudential policy is one of the few clear winners of the crisis, garnering widespread support since the crisis and becoming an increasingly vital part of the policy toolkit in countries around the world. Whether it will be effective in strengthening the resilience of financial systems and preventing financial crises is still an open question (see Galati and Moessner, 2014; Cerutti, Claessens and Laeven, 2017; Cizel et al., 2016).

In principle, macroprudential policies ("MaPs") could have a number of upward or downward effects on income and wealth inequality. If successful, such policies should reduce the probability of financial crises. This would be expected to lower inequality over time: while crises lead in the first instance to losses on financial claims and asset holdings (which are concentrated among the wealthy), they lead thereafter to an increase in unemployment, which affects especially lower incomes (Galbraith and Lu, 1999; Atkinson and Morelli, 2011). Along the same lines, bank capital requirements and financial sector taxes may reduce incentives for rapid growth in the financial sector. Because the financial services sector often pays higher wages than other sectors, the reduction in its size could, *ceteris paribus*, reduce inequality – even if the effects of this trend on economic growth are the subject of heated debate (Cecchetti and Kharroubi, 2012 and 2015; Philippon, 2014; Gennaioli, Shleifer and Vishny, 2014). Conversely, some MaPs have direct redistributive effects – loan-to-value (LTV) and debt-to-income (DTI) limits on mortgages can, for instance, restrict the ability of households with limited financial wealth to purchase a house, and to use a house as collateral for small business investment. This may prevent low-income households from increasing their income or benefiting from price increases, yet it can also shield them from price crashes – and allow greater labor mobility in countries with full recourse mortgages. Finally, MaPs may smooth credit market and asset price developments over the financial cycle, thus reducing the redistribution of wealth due to changes in credit delinquencies and asset valuation changes. They could also mitigate the financial stability risks of international capital flows, thus allowing countries to maintain more open capital accounts.

Whether these plausible effects exist in practice, and whether they are visible at the macro level, is an empirical question. Thanks to new cross-country datasets on macroprudential measures and better data on income inequality, it is now possible for perhaps the first time for researchers to illuminate these relationships in a panel setting. Yet from the outset, any study on macroprudential policy and inequality will be fraught with some serious identification challenges. First, the time period under which macroprudential policy has been used in a sufficiently large sample of countries is short. While some emerging market and developing countries (EMDCs) began using MaPs in the late 1990's or earlier, they only became more widespread in the years immediately preceding 2008, and in advanced economies (AEs) only since the global crisis. The new databases used in this paper begin in the year 2000. Secondly, MaPs are highly heterogeneous, covering a wide range of policy objectives and transmission mechanisms. Aggregating such policies, even in clearly defined sub-groups, necessarily entails lumping together very different policy interventions. Thirdly, identifying the effects of MaPs is challenging at any time, but particularly in a post-crisis environment, in which the financial sector will be undergoing major shifts, unconventional monetary policies are being implemented and numerous other economic changes are happening at once. Fourth, income inequality is a slow-moving indicator, which will at any given point reflect the cumulative effect of a number of economic changes not only in the previous year but in the years and decade prior to that. Finally, because MaPs respond to macro-financial conditions in the country where they are employed, there is potential for problems of endogeneity.

Given all of these challenges, and our use of country-level rather than micro-level data, the ambition level of our study is necessarily limited. We do need seek to find definitive answers on how (specific types of) MaPs affect the overall economy or growth, how persistent the effects are or whether effects can be ascribed cleanly to a causal relationship. Rather, we seek to test, as a first step, whether and in which direction MaPs are *associated* with available measures of inequality. To do this, we regress income inequality, as measured by Solt's (2016) Standardized World Income Inequality Database (SWIID), against data on MaPs from Cerutti, Claessens and Valencia (2017) for 69 countries over the period 2000-2013. Panel regressions offer insights on the association of MaPs with market income inequality, i.e. inequality before government redistribution policies such as taxes and transfers, and net income inequality, or inequality after redistribution. By controlling for economic indicators that are known to affect inequality (e.g. unemployment, financial openness, trade openness, technological change, human capital, etc.), and distinguishing between different types of MaPs and country sub-samples, we seek to derive evidence on the relationships. Given the limitations of macro data for a large country panel, we cannot shed much light on causality, and we purposefully avoid describing our results as causal effects.

Our results suggest a positive relationship between the use of specific macroprudential policies and both market and net income inequality. Specifically, countries that use interbank exposure limits, concentration limits and reserve requirements seem to have a higher Gini coefficient of market and net income inequality in the following year. Moreover, countries that use loan-to-value (LTV) and debt-to-income (DTI) limits seem to have a higher net Gini, but these results are not statistically significant for market inequality, and DTI limits are not robust to alternative specifications. Bank leverage ratios and limits on foreign currency (FX) lending seem to have a negative association with market and net inequality. (The countercyclical capital buffer, additional requirements for systemically important financial institutions (SIFIs) and direct credit growth limits are not considered, as the sample size for these measures is too small to draw strong conclusions). An alternative database of MaPs confirms the positive association of interbank limits, but most other policies are not statistically significant. Finally, we find that especially reserve requirements and LTV limits are associated with a lower income share for the bottom and 5th income deciles (i.e. the poor and the middle class), but a higher income share for the top income decile.

While the mechanisms underlying these results require further investigation, we offer a few potential stories. The first is a political economy trade-off for public authorities between taking macroprudential measures and redistributive measures. It could be that, due to resistance by particular interest groups, authorities are only able to implement a certain number of policy changes, and that MaPs "compete" with further redistributive policies in political decision making processes. This would be consistent with the positive association of LTV and DTI limits net income inequality, but not market inequality. Alternatively, the adverse effects of MaPs on credit conditions for lower-income borrowers may negatively affect their income position or prevent them from benefiting from redistributive policies to the same extent as higher incomes. Finally, in line with Arregui et al. (2013), it is possible that the "leakages" of macroprudential policies may create economic rents, which particularly higher incomes are able to exploit to increase their income and thus income share. This would imply that those MaPs that are relatively more complex or difficult to enforce could be circumvented, with a measurable effect on overall inequality. Each of these explanations is pure conjecture which would have to be examined further through further (preferably micro-level) evidence, or through systematic parsing of causality.

This paper is structured as follows. In section 2, we describe our data set, prima facie evidence and our estimation method. In section 3, we present empirical results of our key panel regressions and alternative measures. Section 4 concludes with our potential interpretations and avenues for future research.

2. Data, prima facie evidence and estimation method

Since the pioneering work of Kuznets (1955), a key finding in the economic literature is that income inequality rises as countries become more developed, only to fall again once income levels rise above a certain threshold (the so-called "Kuznets curve"). Yet since the 1970's, many advanced economies – which should be far above this threshold – have seen an increase in income inequality. A number of explanations for this have been put forward, from skills-biased technological change (see Brown and Campbell, 2002, for a summary) to public policy changes (Schmitt, 2009), capital account liberalization (Furceri and Loungani, 2015) and the growth of the financial sector (Cournède, Denk and Hoeller, 2015).[1] Recently, Jaumotte, Lall and Papageorgiou (2013) and Dabla-Norris et al. (2015) have developed integrated frameworks for estimating the drivers of inequality in a panel setting. These studies include indicators of e.g. trade and financial openness, technological change, human capital, employment shares, and country and year fixed effects to control for cross-country differences and common shocks.

Analysis of income inequality in a cross-county setting is hampered in part by the challenges of measuring inequality. While many countries collect data on income distributions, there are substantial differences in definitions, sampling and frequency. Together, these make it difficult to do panel regression analysis. This has been improved significantly by the work of Piketty (2014) and by the Standardized World Income Inequality Database (SWIID), compiled by Frederick Solt (2016). The SWIID makes a distinction between market income inequality, measured as a Gini coefficient of income prior to government redistribution policies, and net income inequality, which results after redistribution. The difference between

[1] None of these explanations is universally accepted, and especially the role of financial development is still the subject of significant research. Demirgüç-Kunt and Levine (2009) lay theoretical and empirical groundwork for a downward effect of financial development on inequality, while Claessens and Perotti (2007) show how financial liberalization in developing countries can actually increase fragility and inequality, through "capture" of reforms by established interests. More recently, De Haan and Sturm (2016) show that financial development and liberalization tend to increase inequality, but that the level of financial development conditions the impact of financial liberalization on inequality. De Haan and Sturm (2015) show there is no robust link between economic freedom and market inequality, but that countries with high ethno-linguistic fractionalization redistribute less.

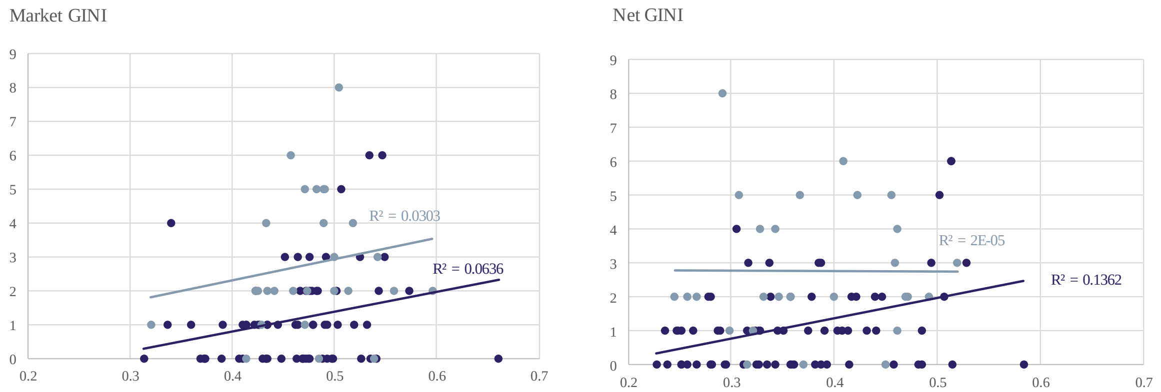
the two series measures the scale of redistribution, relative to the initial market allocation.[2] The data allow one to disentangle market outcomes from final disposable income inequality, which has yielded new insights in the literature on the effects of inequality. An example is the study by Ostry, Berg and Tsangarides (2014), who find that lower net inequality is robustly correlated with faster and more durable economic growth, for a given level of redistribution.

The data on macroprudential policy across countries have until now been even more sparse, but have recently seen substantial development. Thanks to the IMF's Global Macroprudential Policy Instruments (GMPI) survey, several new databases have emerged with broad coverage and high frequency of macroprudential instruments across countries. One, by Cerutti, Claessens and Laeven (2017; abbreviated here as CCL) converts the GMPI data into an annual panel for 119 countries. They cover 12 types of macroprudential policy instruments, which are subdivided into borrower-based measures, such as loan-to-value (LTV) and debt-to-income (DTI) limits, and financial institution-based measures, which comprise most other tools (e.g. counter-cyclical capital buffers and dynamic provisioning, capital surcharges on systemically important financial institutions, levies or taxes on specific assets or (non-core) liabilities, etc.). More recently, Cerutti, Correa, Fiorentino and Segalla (2017; abbreviated as CCFS) have gone even further, converting the data into quarterly frequency and identifying tightening and loosening measures. These data also have a broader coverage of policies, considering general bank capital requirements and other prudential measures that are not typically considered macroprudential. However, these data are only available for 64 countries, and exclude some categories of macroprudential measures such as taxes on financial institutions. In the following, we use CCL as our key measure, and CCFS as a robustness check.

Figure 1 shows prima facie evidence of the relationship between the use of macroprudential measures and inequality. Observations in the year 2000 are denoted by blue dots, while those in 2013 are marked in grey. There is a mild positive relationship between the two variables in both the left and right panel, indicating that countries with more MaPs in place generally have higher market and net income inequality (with the exception of net inequality in 2013). Interestingly, this relationship was already apparent in 2000, even though there were far fewer measures in place in that year than in 2013. In what follows, this relationship is analyzed more systematically with appropriate control variables.

[2] Moreover, in order to capture uncertainty around the estimations, the SWIID contains 100 separate imputations for each series; such multiply imputed data capture the range of possible Gini coefficients. Here, in order to simplify the programming and economize on computing time, we simply take the mean of all imputations. For the regressions, we have found that our results are robust to using multiple imputations.

Figure 1: Number of macroprudential measures and inequality in 2000 and 2013



Note: The blue dots denote data for the year 2000, while data for 2013 are marked grey.
Source: Standardized World Income Inequality Database (SWIID); Cerutti, Claessens and Laeven (2017)

2.1. Estimation method

In order to test the relationship between income inequality and macroprudential measures, we use a panel regression framework. We estimate the Gini coefficient with the equation:

$$Gini_{i,t} = \alpha_i + \beta_1 MaP_{i,t-1} + \beta_2 X_{i,t-1} + \gamma_i + \varepsilon_{i,t}$$

where $Gini_{i,t}$ is the net or market measure of income inequality, α_i and γ_i are country and year fixed effects and $X_{i,t-1}$ is a vector of lagged control variables that should have an impact on income inequality.[3] Building on Jaumotte, Lall and Papageorgiou (2013) and Dabla-Norris et al. (2015), the control variables include: (i) trade openness, as measured by the ratio of exports and exports to GDP; (ii) capital account openness which is relevant given the positive relationship between capital account liberalization and inequality found by Furceri and Loungani (2015); (iii) domestic credit to GDP; (iv) the ratio of the information and communications technology (ICT) capital stock to GDP (Jorgenson and Vu, 2013); (v) human capital, as measured by the average years of schooling in the population; (vi) government expenditure on cash transfers and subsidies; (vii) employment shares in the industrial and services sectors. Moreover, given the strong cyclical impact of unemployment on inequality,

[3] All variables are lagged by one year so as to address simultaneity.

we include the unemployment rate in the controls. We control for the impact of banking crises with a dummy equal to 1 in the five years following a banking crisis.[4]

Our innovation relative to earlier research is to add to the estimation $MaP_{i,t-1}$, a vector of lagged macroprudential policies, to assess their association with income inequality. A priori, it is not clear whether different categories of MaPs should be included simultaneously or one at a time. The former approach may help to ensure a complete picture and mitigate omitted variable bias; the latter approach may help isolate overall effects, given the tendency of authorities to use multiple categories of MaPs. In what follows, we will use both approaches. Where specific categories of MaPs have been used only infrequently, we do not include these categories in the regressions. Throughout, we estimate the relationships in a general least squares (GLS) framework with fixed effects. A Hausman test shows that random effects would be consistent, but we prefer fixed effects due to country differences in institutions and measurement of inequality (e.g. disposable income vs. consumption). All standard errors are clustered at the country level.

Our approach helps to identify associations, but it does not pinpoint causality or clarify the dynamics of the associations. In order to isolate causality, it could be useful to proceed in a two-stage approach. For example, in a propensity score matching (PSM) framework, the probability that a country will take a new measure can be estimated in a first stage, and countries subsequently compared between a treatment and control group. This method, while promising, relies on accurate prediction of MaPs in the first stage, which has not yet yielded reliable results.[5] To assess the dynamics of inequality measures after MaPs, one could use panel local projection methods, as in Jorda (2005). This is hampered in the current dataset by the low variation among most measures, which makes for too few observations of policy events. Both issues should be mitigated as further data on MaPs becomes available, i.e. with further use and data collection. As such, we leave these methods as potential avenues for future research.

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[4] An earlier version of this paper followed Lee (2006) and used GDP per capita and its quadratic term as key control variables, as a means of testing the Kuznets relationship. The results for MaPs from this specification are consistent with the new baseline, but there are a number of potential criticisms of omitted variable bias. We have also tried inflation, shown by Albanesi (2007) to have a positive association with income inequality; population growth, which may increase income inequality through the effects of a growing labor force on wages; and the credit gap, i.e. divergence of credit-to-GDP ratio from its trend (Drehmann and Tsatsaronis, 2014), but find these controls generally to be insignificant when controlling for other factors.

[5] We would expect that MaPs are more likely when credit growth is high, due to the higher probability of crisis (Schularick and Taylor, 2012), when lagged corporate credit spreads are compressed (López-Salido et al., 2015), or when the bank z-score is low, reflecting banking system vulnerability, but these effects are not yet borne out empirically.

2.2. Descriptive statistics and correlations

The data for net and market Gini coefficients and MaPs are as described above. When matching the datasets, we end up with useable data for 69 countries over 14 years (2000-2013). While we exclude countries with less than 8 years of data on MaPs, we still end up with an unbalanced panel due to some missing observations in early years of the sample or for the most recent years. The market and net Gini coefficients take a value between 0 (perfect equality) and 100 (perfect inequality). Table 1 gives descriptive statistics.

Table 1: Descriptive statistics

	Observations	Mean	Std. Dev.	Minimum	Maximum
Net Gini (SWIID)	903	35.88	8.21	21.31	59.66
Market Gini (SWIID)	903	46.67	5.48	31.29	68.01
Loan-to-value limits (CCL)	966	0.21	0.41	0	1
Debt-to-income limits (CCL)	966	0.11	0.32	0	1
Dynamic loan loss provisioning (CCL)	966	0.07	0.26	0	1
Countercyclical capital buffers (CCL)	966	0.01	0.09	0	1
Leverage ratio requirements (CCL)	966	0.10	0.30	0	1
SIFI requirements (CCL)	966	0.01	0.09	0	1
Interbank exposure limits (CCL)	966	0.30	0.46	0	1
Concentration limits (CCL)	966	0.58	0.49	0	1
Foreign currency lending limits (CCL)	966	0.13	0.34	0	1
Reserve requirements (CCL)	966	0.22	0.41	0	1
Direct credit growth limits (CCL)	966	0.05	0.21	0	1
Financial sector levies and taxes (CCL)	966	0.12	0.32	0	1
Macroprudential Policy Index (CCL)	966	1.77	1.66	0.00	8.00
Macroprudential Policy Index (CCFS)	686	3.80	4.62	0	26
Unemployment (WDI)	966	8.23	4.88	0.10	35.90
Trade openness (WDI)	966	92.20	62.68	20.26	455.28
C.A. openness (Chinn-Ito)	966	1.10	1.42	-1.89	2.39
Domestic credit (WDI)	939	0.64	0.44	0.00	3.12
ICT capital stock (JV)	897	3.26	1.38	0.54	8.21
Human capital (PWT)	966	2.84	0.56	1.54	3.73
Gov. Expenditure (WDI)	841	26.34	11.48	1.22	134.77
Industrial employment (WDI)	876	24.43	6.39	4.40	42.30
Service employment (WDI)	876	59.77	13.68	13.30	87.00
Banking crisis (LV)	966	0.14	0.35	0	1
Banking sector z-score (WDI)	942	17.44	11.82	-7.93	74.13

The MaP indicators from CCL are dummy variables that take on a value of 1 when a particular measure is used. Of the 12 categories, we find that countries use an average of 1.8 types of policies in any given year. Concentration limits, which prevent banks from building up large exposures to specific borrowers, are the most common type of measure, followed by interbank exposure limit and (countercyclical and FX) reserve requirements.[6] These measures could reduce bank interconnectedness and connected lending, but may also be relatively more complex to administer and more prone to "leakages" than traditional bank capital requirements. Borrower-based measures, i.e. LTV and DTI limits, are used with some frequency for real estate markets, and may be expected to constrict the borrowing ability of borrowers without extensive income or collateral. Dynamic loan loss provisioning, used for example in Spain before the crisis, may restrict dividends of banks during periods of high profitability, which could impact the income position of bank shareholders. Meanwhile, countercyclical capital buffers, requirements for systemically important financial institutions (SIFIs) and direct credit growth limits are used so sparsely that their inclusion in regressions would be problematic, as it may capture specific country or year characteristics. Unfortunately, the variables do not tell us about the intensity of various measures, i.e. the extent to which they are binding. However, CCL also generate an aggregate index, which is simply the sum of the 12 dummies, ranging from 0 to 8 in our sample.[7] The alternative CCFS database codes MaPs based on successive tightening or loosening in any of its 10 categories of measures. Because of the relatively high frequency of such changes, the index varies between 0 and 26, with a mean of nearly 4 past tightening measures in any given country and year. Meanwhile, several of the control variables are taken from the Penn World Tables (PWT) or the World Bank's World Development Indicators (WDI). Banking crises come from the database of Laeven and Valencia (2013; abbreviated as LV). We define a dummy for the year in which a banking crisis has taken place and subsequent years in a 5-year period, to control for the persistent effects of banking crises on the income distribution. Capital account openness is measured with the index of Chinn and Ito (2006).[8] The banking sector z-score, which corresponds to the "distance to default" or resilience of a country's banking sector, is included to capture the systemic vulnerabilities that macroprudential policies often are meant to respond to. Correlations between the key variables (table 2) show that a panel regression is feasible without significant issues of multicollinearity.

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[6] While there is also a broader category of reserve requirements, we focus on those requirements with a macroprudential character, such as the FX and/or countercyclical reserve requirements used, for example, in Brazil, Peru and Serbia.

[7] This index was used as the key independent variable in earlier versions of this paper. Yet this may be problematic for a number of reasons, including the underlying assumption that the categories of MaPs are homogenous and that the relationship with inequality follows a linear pattern. This may not hold in practice. As such, this index will only be used in robustness checks. The countries with the highest number of MaPs include Pakistan (8 measures, 2008-2013), China (8 measures, 2013), and Colombia (7 measures, 2007-2013).

[8] Consistent results are obtained when using the newer database of Fernandez et al. (2015), which codes the number of restrictions on specific flows, but we lose observations due to the lower country and year coverage.

Table 2: Correlations between key variables

	Net Gini	Market Gini	Unemploy-ment	Trade openness	C.A. openness	Dom. credit / GDP	ICT capital stock	Human capital	Gov. Expendi-ture	Industrial employ-ment	Service employ-ment	Banking sector z-score
Net Gini	1.00											
Market Gini	0.53	1.00										
Unemployment	0.10	0.28	1.00									
Trade openness	-0.02	-0.02	-0.13	1.00								
C.A. openness	-0.28	0.14	-0.13	0.17	1.00							
Dom. credit / GDP	-0.29	0.00	-0.22	0.29	0.37	1.00						
ICT capital stock	-0.04	0.33	-0.02	0.20	0.34	0.31	1.00					
Human capital	-0.62	-0.10	-0.01	0.15	0.45	0.40	0.33	1.00				
Gov. expenditure	-0.44	0.02	0.08	-0.07	0.24	0.26	0.14	0.31	1.00			
Industrial employment	-0.32	-0.04	0.08	0.03	0.12	0.02	0.09	0.27	0.17	1.00		
Service employment	-0.22	0.19	-0.10	0.22	0.56	0.60	0.47	0.57	0.31	0.08	1.00	
Banking sector z-score	-0.01	0.09	0.04	0.02	0.23	0.02	0.13	0.13	0.04	0.04	0.12	1.00

3. Empirical results

Having defined our estimation framework and described the data, we move on to our empirical estimation results. In what follows, we consider regressions in which MaPs are added to these regressions, first with all categories simultaneously (section 3.1) and then separately (3.2). We proceed to look at alternative measures of inequality and MaPs (section 3.3).

3.1. Regressions of all macroprudential instruments simultaneously

Table 3 shows regression results for the market measure of income inequality. To ensure that we are correctly controlling for key variables, we have embarked from a model without data on MaPs (columns 1 and 2). These estimations confirm a positive association of market inequality with lagged unemployment, and also with financial development, as measured by the ratio of domestic credit to GDP. Trade and capital account openness, technological change, human capital and government expenditure have the expected sign, but are not significant with clustered standard errors.[9] Similarly, banking sector z-score (which reflects higher banking system resilience) has a negative but insignificant association with inequality.

[9] These variables are found by Dabla-Norris et al. (2015) to have a heterogeneous impact on AEs versus EMDCs. Particularly for net income inequality, we can confirm that this interaction matters, as government expenditure seems to be associated with lower inequality only in AEs and not in EMDCs.

Table 3: Baseline estimations for market income inequality

VARIABLES	(1) Baseline model	(2) Full model	(3) Baseline model with MaPs	(4) Full model with MaPs	(5) AEs	(6) EMDEs
Categories of MaPs						
Loan-to-value limits			0.396	0.494	0.219	1.468
			(0.552)	(0.660)	(0.533)	(1.017)
Debt-to-income limits			0.982	1.105	-0.856	1.885
			(0.965)	(1.049)	(0.924)	(1.128)
Dynamic loan loss provisioning			-0.734	-0.615		-1.243
			(1.187)	(1.280)		(0.933)
Leverage ratio requirements			-3.306***	-3.673***	-0.0994	-4.179***
			(0.793)	(0.999)	(0.861)	(1.147)
Interbank exposure limits			0.928	1.163*	0.319	1.164
			(0.644)	(0.648)	(0.565)	(1.034)
Concentration limits			2.340**	2.408*	0.864	3.077*
			(1.024)	(1.291)	(0.713)	(1.711)
Foreign currency lending limits			-1.073*	-1.537*	-0.335	-2.234
			(0.629)	(0.775)	(0.708)	(1.329)
FX/countercyclical reserve requirements			1.907**	1.994**		1.406
			(0.906)	(0.829)		(0.949)
Financial sector levies and taxes			-0.517	-0.532	-0.675	-0.925
			(0.743)	(0.741)	(0.880)	(1.368)
Controls						
Unemployment	0.201**	0.198**	0.195**	0.190**	0.241*	0.0516
	(0.0850)	(0.0842)	(0.0838)	(0.0855)	(0.127)	(0.0827)
Trade openness	0.0121	0.0106	0.0125	0.00579	-0.00838	0.0148
	(0.0148)	(0.0155)	(0.0134)	(0.0145)	(0.0182)	(0.0143)
C.A. openness	0.108	0.0395	-0.0754	-0.0314	-0.340	0.148
	(0.313)	(0.290)	(0.225)	(0.216)	(0.436)	(0.278)
Dom. credit / GDP	2.935**	2.766	2.797**	3.291	1.367*	4.231
	(1.258)	(3.386)	(1.156)	(2.938)	(0.778)	(2.704)
Human capital	0.672	-0.257	1.322	-0.879	4.694	1.853
	(3.773)	(4.263)	(3.272)	(3.820)	(3.163)	(6.206)
ICT capital stock	0.281	0.280	0.0807	0.170	0.345	0.593
	(0.344)	(0.405)	(0.344)	(0.408)	(0.452)	(0.733)
Gov. expenditure	0.0204	0.0388***	0.0195	0.0360***	-0.0431	0.0315***
	(0.0274)	(0.0117)	(0.0238)	(0.00905)	(0.0450)	(0.00876)
Banking crisis	0.595*	0.678**	0.696**	0.714**	1.464***	-0.945**
	(0.327)	(0.299)	(0.330)	(0.337)	(0.350)	(0.364)
Dom. credit / GDP * AE		-0.534		-0.914		
		(3.580)		(3.084)		
Human capital * AE		6.428		6.471		
		(4.356)		(3.957)		
Gov. expenditure *AE		-0.102*		-0.0693		
		(0.0570)		(0.0597)		
Industrial employment		0.00276		-0.0155	0.288*	-0.0203
		(0.0629)		(0.0600)	(0.144)	(0.0638)
Service employment		0.0208		0.00608	0.313***	-0.0145
		(0.0244)		(0.0417)	(0.0990)	(0.0494)
Banking sector z-score		-0.00272		-0.00551	-0.00314	0.0115
		(0.0135)		(0.0134)	(0.0135)	(0.0273)
Observations	775	699	728	662	347	315
R-squared	0.157	0.205	0.241	0.267	0.430	0.317
Number of countries	69	68	69	68	30	38
r2 within	0.157	0.205	0.241	0.267	0.430	0.317
r2 between	0.026	0.003	0.002	0.003	0.000	0.007

Note: estimated coefficients of GLS panel regressions with country and year fixed effects. Significance at 10%, 5% and 1% level denoted with *, ** and ***. All independent variables have a lag of one year. Constants are not reported.

When we add the various categories of MaPs from the CCL database (Table 3, columns 3 and 4), three types of policies enter with a positive coefficient. Specifically, we find a strong positive association of concentration limits and reserve requirements with inequality. In the full model, we also find a positive coefficient for interbank exposure limits. Notably, each of these measures are financial institution-based limits, which have been used particularly in EMDEs over the sample period and have relatively complex guidance and governance relative to other measures. In economic terms, the use of concentration limits, reserve requirements and interbank exposure limits is associated with a Gini coefficient that is 2½, 2 and 1 points higher, respectively. Conversely, we find a strong negative coefficient for leverage ratio requirements, and for limits on FX lending. LTV and DTI limits have positive but insignificant coefficients, while dynamic loan loss provisioning and financial sector levies and taxies have negative and insignificant coefficients. The coefficient of banking crises is significantly positive, meaning that countries with a recent crisis have market inequality which is almost a percentage point higher than in comparable countries. When looking at AEs (column 3) we see generally consistent signs of the coefficients, but they are not significant, due perhaps to the lower number of observations for AEs. For EMDEs (column 4), we find that LTV and DTI limits have positive coefficients that are just short of statistical significance.[10]

For net income inequality (table 4), the positive associations extend to different variables, while the negative associations are largely the same. In the baseline model, we see significantly positive coefficients for concentration limits, and for LTV and DTI limits. (Interbank exposure limits and reserve requirements are no longer significant). In economic terms, the use of LTV limits is associated with a Gini index of net income inequality that is about ¾ of a percentage point higher than in other countries, while DTI limits are associated with a Gini coefficient that is 1 ½ to 2 points higher. When we look only at EMDEs (column 4), the coefficients are even higher, entailing a Gini which is 2-3 percentage points higher for these borrower-based measures. Among controls, banking crises maintain their positive coefficient (except for EMDEs), meaning that crises are also deleterious for income equality after redistribution, when controlling for the level of government expenditure.

[10] The separate regressions for AEs and EMDEs are merely for purposes of illustration. The differences in the coefficients between the two sub-samples are generally not statistically significant. The same holds for differences between democracies and non-democracies, and countries where the central bank controls MaPs vs those where MaPs are controlled by a different authority.

Table 4: Baseline results for net income inequality

VARIABLES	(1) Baseline model	(2) Full model	(3) Baseline model with MaPs	(4) Full model with MaPs	(5) AEs	(6) EMDEs
Categories of MaPs						
Loan-to-value limits			0.712*	0.799*	0.505	1.786**
			(0.380)	(0.447)	(0.328)	(0.713)
Debt-to-income limits			1.476**	1.995***	-0.0906	2.814***
			(0.648)	(0.669)	(0.435)	(0.709)
Dynamic loan loss provisioning			-1.526	-1.616		-1.785**
			(1.018)	(1.037)		(0.771)
Leverage ratio requirements			-1.585*	-1.937**	1.151	-2.866***
			(0.882)	(0.906)	(0.823)	(0.832)
Interbank exposure limits			0.350	0.598	-0.713	1.368
			(0.725)	(0.893)	(1.098)	(0.847)
Concentration limits			1.759*	2.047*	1.621**	2.335
			(0.948)	(1.158)	(0.784)	(1.572)
Foreign currency lending limits			-0.727	-0.891	0.688	-2.384***
			(0.703)	(0.731)	(0.447)	(0.624)
FX/CTC Reserve requirements			-0.0749	0.0205		0.129
			(0.648)	(0.612)		(0.636)
Financial sector levies and taxes			0.176	0.0441	-0.292	-0.0687
			(0.415)	(0.404)	(0.524)	(0.985)
Controls						
Unemployment	0.0347	0.0239	0.00669	-0.00755	-0.00230	-0.0249
	(0.0576)	(0.0534)	(0.0581)	(0.0563)	(0.0842)	(0.0720)
Trade openness	0.00464	0.00685	0.00356	0.000322	-0.0203	0.0112
	(0.0117)	(0.0132)	(0.0111)	(0.0123)	(0.0152)	(0.0134)
C.A. openness	0.230	0.179	0.152	0.243	0.371	0.114
	(0.239)	(0.246)	(0.188)	(0.174)	(0.220)	(0.215)
Dom. credit / GDP	1.196	-0.274	1.054	-0.658	0.436	0.225
	(0.735)	(2.561)	(0.676)	(2.124)	(0.711)	(2.015)
Human capital	-1.115	-1.243	-0.754	-1.911	-1.063	1.040
	(3.164)	(3.761)	(2.702)	(3.175)	(2.276)	(5.314)
ICT capital stock	0.343	0.394	0.190	0.348	0.441	0.583
	(0.303)	(0.335)	(0.288)	(0.328)	(0.329)	(0.586)
Gov. expenditure	0.00929	0.0331***	-0.00187	0.0272**	-0.0770***	0.0266***
	(0.0277)	(0.0113)	(0.0294)	(0.0107)	(0.0226)	(0.00738)
Banking crisis	0.545*	0.638**	0.555**	0.652**	0.839**	-0.0452
	(0.293)	(0.284)	(0.270)	(0.291)	(0.395)	(0.423)
Dom. credit / GDP * AE		1.489		2.023		
		(2.659)		(2.195)		
Human capital * AE		3.189		2.556		
		(3.121)		(2.732)		
Gov. expenditure *AE		-0.112***		-0.0985***		
		(0.0272)		(0.0255)		
Industrial employment		-0.0112		-0.0256	0.175	-0.0538
		(0.0651)		(0.0563)	(0.106)	(0.0529)
Service employment		-0.0237		-0.0393	0.162**	-0.0491
		(0.0242)		(0.0330)	(0.0744)	(0.0363)
Banking sector z-score		0.00486		0.000627	0.00238	0.0107
		(0.0120)		(0.0103)	(0.00937)	(0.0223)
Observations	775	699	728	662	347	315
R-squared	0.065	0.127	0.174	0.235	0.269	0.376
Number of countries	69	68	69	68	30	38
r2 within	0.0654	0.127	0.174	0.235	0.269	0.376
r2_between	0.0259	0.00270	0.00175	0.00297	1.09e-06	0.00684

Note: estimated coefficients of GLS panel regressions. Significance at 10%, 5% and 1% level denoted with *, ** and ***. All independent variables have a lag of one year. Constants are not reported.

3.2. Categories of macroprudential instruments separately

Due to the considerations described in section 2.1, we also consider the categories of MaPs separately. Table 5 shows the results for market inequality, and table 6 shows results for net income inequality. In these regressions, the controls (not reported) are the same as in the "full" model above.

Again starting with market inequality, we find a positive coefficient only for reserve requirements. Interbank limits and concentration limits have a coefficient which is positive but just shy of statistical significance at the 90% level. LTV and DTI limits have a positive but insignificant coefficient. Limits on foreign currency lending have a significantly negative association. The leverage ratio has a negative coefficient that is just short of statistical significance at the 90% level.

Table 5. Regressions for level of Gini of market income inequality

VARIABLES	LTV	DTI	DP	LEV	INTER
Macroprudential measure	0.643	0.880	0.0627	-2.043	0.934
	(0.656)	(1.134)	(1.686)	(1.378)	(0.561)
Observations	662	662	662	662	662
Number of countries	68	68	68	68	68
r2 within	0.192	0.193	0.188	0.199	0.193
r2_between	0.00396	0.00380	0.00384	0.00355	0.00329

VARIABLES	CONC	FC	RR	TAX
Macroprudential measure	1.706	-1.336**	1.541**	-0.557
	(1.180)	(0.604)	(0.760)	(0.779)
Observations	662	662	662	662
Number of countries	68	68	68	68
r2 within	0.206	0.197	0.192	0.190
r2 between	0.00298	0.00542	0.00364	0.00388

Note: estimated coefficients of GLS panel regressions with country and year fixed effects. Significance at 10%, 5% and 1% level denoted with *, ** and ***. All independent variables have a lag of one year. Controls are as in column 2 of table 3, but are omitted for brevity. Abbreviations: LTV = loan-to-value limits; DTI = debt-to-income limits; DP = dynamic loan loss provisioning; LEV = leverage ratio requirements; INTER = interbank exposure limits; CONC = concentration limits; FC = limits on foreign currency lending; RR = FX/countercyclical reserve requirements; TAX = financial sector levies and taxes.

Yet again, there are notable differences in the results for inequality after redistribution. When looking at the coefficients by instrument for net income inequality (table 6), we find that LTV and DTI limits, as well as countercyclical capital requirements, concentration limits and direct credit growth limits all have significant positive coefficients. The leverage ratio and limits on FX loans have negative coefficients, but these are not significant.

Table 6. Regressions for level of Gini of net income inequality

VARIABLES	LTV	DTI	DP	LEV	INTER
Macroprudential measure	1.205***	1.963***	-1.427	-0.805	0.606
	(0.402)	(0.660)	(1.286)	(1.290)	(0.880)
Observations	662	662	662	662	662
Number of countries	68	68	68	68	68
r2 within	0.137	0.158	0.129	0.118	0.119
r2_between	0.172	0.197	0.120	0.202	0.212

VARIABLES	CONC	FC	RR	TAX
Macroprudential measure	1.494	-0.287	-0.430	0.339
	(1.020)	(0.693)	(0.347)	(0.512)
Observations	662	662	662	662
Number of countries	68	68	68	68
r2 within	0.138	0.115	0.115	0.116
r2 between	0.183	0.208	0.205	0.204

Note: estimated coefficients of GLS panel regressions with country and year fixed effects. Significance at 10%, 5% and 1% level denoted with *, ** and ***. All independent variables have a lag of one year. Controls are as in column 3 of table 4, but are omitted for brevity. Abbreviations: LTV = loan-to-value limits; DTI = debt-to-income limits; DP = dynamic loan loss provisioning; LEV = leverage ratio requirements; INTER = interbank exposure limits; CONC = concentration limits; FC = limits on foreign currency lending; RR = FX/countercyclical reserve requirements; TAX = financial sector levies and taxes.

Overall, the disaggregated estimations show once again that the relationship of MaPs is stronger with net inequality than with market inequality, and that especially borrower-based instruments such as LTV and DTI limits appear to have a positive association with net inequality.

3.3. Alternative measures of MaPs and inequality

As a robustness check, we measure MaPs with the alternative CCFS database which, despite lower coverage, is able to capture tightening and loosening of MaPs and hence the intensity of the overall macroprudential stance. Moreover, given the well-known problems with measuring inequality through an annual Gini coefficient, we perform checks with an alternative dependent variable: income shares by decile, taken from the United Nations University World Income Inequality Database (UNU-WIDER).

Table 7 shows regressions of market inequality with the CCFS data. Here, we can confirm the positive coefficient of interbank exposure limits, to the tune of 1 percentage point of Gini per successive tightening measure in the baseline model (not significant in the full model). For reserve requirements and LTV limits, we find positive coefficients, thought these are not significant. Sector-specific capital requirements for construction have a negative coefficient (with a small sample size) and overall capital requirements and concentration limits have a negative coefficient that is close to significance. Notably, LTV and interbank limits have a positive coefficient, significant at the 95% level for EMDEs, and overall capital requirements have a significant negative coefficient for this group.

Table 7. Regressions for market income inequality using CCFS database

VARIABLES	(1) Baseline model	(2) Full model	(3) AEs	(4) EMDEs
Categories of MaPs				
Reserve requirements (LC)	0.196	0.0808	-0.0769	-0.101
	(0.618)	(0.657)	(0.909)	(0.703)
Reserve requirements (FX)	0.657	1.125	0.867	1.617
	(0.820)	(0.923)	(1.125)	(1.072)
LTV limits	1.085	0.637	1.091	1.535**
	(0.781)	(0.739)	(0.805)	(0.641)
Interbank exposure limits	0.960*	0.714	0.0651	1.970**
	(0.570)	(0.565)	(0.489)	(0.970)
Concentration limits	-0.855	-0.176	-0.174	0.264
	(0.526)	(0.523)	(0.500)	(1.115)
Overall capital requirements	-0.943	-0.808	-0.0719	-1.935**
	(0.641)	(0.604)	(0.720)	(0.747)
Sector-specific capital	0.337	0.405	0.199	0.968
requirements (real estate)	(0.696)	(0.689)	(0.634)	(0.951)
Sector-specific capital	-2.432*	-2.332*	-3.734*	-1.790
requirements (construction)	(1.445)	(1.344)	(1.978)	(1.499)
Sector-specific capital	1.674	2.129*	2.127**	1.869
requirements (other)	(1.108)	(1.202)	(0.822)	(1.593)
Selected controls				
Banking crisis	0.564*	0.657**	1.544***	-1.032**
	(0.309)	(0.262)	(0.421)	(0.487)
Banking sector z-score		-0.00232	-0.00175	0.00772
		(0.0132)	(0.00995)	(0.0309)
Observations	775	699	364	335
R-squared	0.199	0.247	0.446	0.258
Number of countries	69	68	30	38
r2 within	0.199	0.247	0.446	0.258
r2_between	0.0326	0.00252	0.000400	0.0270
r2 overall	0.0471	2.55e-05	0.0162	0.0495

Note: estimated coefficients of GLS panel regressions. Significance at 10%, 5% and 1% level denoted with *, ** and ***. All independent variables have a lag of one year. Controls are as in table 3.

Table 8 presents the coefficients of MaPs and controls for the income shares of low incomes (bottom decile; columns 1-2); the middle class (5^{th} decile; columns 3-4) and high incomes (top decile; columns 5-6). These data concern disposable income, which generally takes into account government taxes and transfers, and hence correspond best to the net inequality measures. For reserve requirements, we find a negative coefficient for the bottom decile, meaning that the poorest have a lower income share (by about ¼ to 1/3 of a percentage point) in countries and periods with these measures in place. For LTV limits, we find a negative coefficient for the 5th decile (the middle class), and a positive coefficient for the top decile. In economic terms, high incomes see their income share rise by about 1.5-1.6 percentage points when LTV limits in place. Together, these results show that the poor are poorer and the rich are richer than without MaPs in place, controlling for all else. Conversely, upper incomes seem to have a lower income share when dynamic provisioning is in place, consistent with results for EMDEs in table 4.

Table 8. Regressions for different income shares

VARIABLES	(1) 1st decile - Baseline model	(2) 1st decile - Full model	(3) 5th decile - Baseline model	(4) 5th decile - Full model	(5) 10th decile - Baseline model	(6) 10th decile - Full model
Loan-to-value limits	-0.115	-0.142	-0.208	-0.230*	1.493**	1.642**
	(0.132)	(0.143)	(0.125)	(0.115)	(0.601)	(0.670)
Debt-to-income limits	-0.211	-0.107	-0.0226	0.0336	0.208	0.207
	(0.259)	(0.212)	(0.156)	(0.110)	(0.896)	(0.831)
Dynamic loan loss provisioning	0.172	0.111	0.0828	0.152	-1.429	-1.532*
	(0.121)	(0.121)	(0.182)	(0.152)	(0.948)	(0.894)
Leverage ratio requirements	0.0753	0.210	-0.0692	0.0774	0.378	0.158
	(0.242)	(0.228)	(0.157)	(0.136)	(0.785)	(0.820)
Interbank exposure limits	0.285	0.0389	0.376	0.0508	-1.315	0.163
	(0.287)	(0.203)	(0.311)	(0.144)	(1.395)	(0.838)
Concentration limits	-0.236	-0.259	-0.0786	-0.0316	0.495	0.322
	(0.237)	(0.194)	(0.125)	(0.132)	(0.911)	(0.939)
Foreign currency lending limits	0.0281	-0.0196	-0.00555	-0.0217	-0.274	0.186
	(0.115)	(0.131)	(0.0679)	(0.0592)	(0.501)	(0.449)
Reserve requirements	-0.247**	-0.338***	0.0241	-0.0478	-0.174	0.175
	(0.103)	(0.0944)	(0.106)	(0.0671)	(0.516)	(0.407)
Financial sector levies and taxes	0.0125	0.00176	-0.222	-0.0856	0.191	-0.128
Observations	347	347	333	333	346	346
Number of countries	58	58	51	51	58	58
r2 within	0.192	0.194	0.272	0.295	0.218	0.246
r2 between	0.0812	0.0791	0.166	0.179	0.126	0.135
r2 overall	0.248	0.244	0.208	0.236	0.213	0.242

Note: estimated coefficients of GLS panel regressions with country and year fixed effects. Significance at 10%, 5% and 1% level denoted with *, ** and ***. All independent variables have a lag of one year.

4. Conclusions

In this study, we have examined the relationship between net and market income inequality and macroprudential policies for a panel of 69 advanced and emerging market and developing economies over the period 2000 to 2013. This type of analysis is made possible by the recent release of consistent cross-country data on both inequality and MaPs. Overall, our findings suggest a positive relationship between the use of some MaPs and both market and net income inequality. Countries that use interbank exposure limits, concentration limits and macroprudential reserve requirements seem to have a higher Gini coefficient of market and net income inequality in the following year. Countries that use loan-to-value (LTV) and debt-to-income (DTI) limits seem to have a higher Gini of net income inequality, but these results are not statistically significant for market inequality. The leverage ratio and limits on foreign currency (FX) lending seem to have a negative association with market and net inequality, particularly in EMDEs. An alternative database of MaPs confirms the positive association of interbank limits, but most other policies are not statistically significant. Finally, reserve requirements and LTV limits are associated with a lower income share for the bottom and 5th income deciles (i.e. the poor and the middle class), but a higher income share for the top income decile.

The results identified here are associations, and substantially more work must be done to isolate causality. One option would be to use propensity score matching to compare countries that have taken MaPs with similar countries that had no such policy action. Another option is an analysis of the market and net earnings of different groups, ideally at the micro level, by age, geography or level of education and, where possible, data on wealth inequality. This type of analysis would be easier at the country level than in a cross-country panel, where there are limits to what can be teased out of the data. These initial results are thus above all an invitation to further research.

References

Albanesi, Stefania (2007), "Inflation and inequality," *Journal of Monetary Economics* 54(4): 1088-1114.

Arregui, Nicolas, Jaromír Beneš, Ivo Krznar, Srobona Mitra and Andre Oliveira Santos (2013), "Evaluating the Net Benefits of Macroprudential Policy: A Cookbook," IMF Working Paper No. 13/167.

Atkinson, Anthony B. and Salvatore Morelli (2011), "Economic crises and Inequality," United Nations Development Programme Occasional Paper No. 2011/06.

Atkinson, Anthony B. (2015), *Inequality: What Can Be Done?* Cambridge, MA: Harvard University Press.

Brown, Clair and Benjamin A. Campbell (2002), "The Impact of Technological Change on Work and Wages," *Industrial Relations: A Journal of Economy and Society* 41(1): 1-33.

Cecchetti, Stephen and Enisse Kharroubi (2012), "Reassessing the impact of finance on growth," BIS Working Paper No. 381.

--- (2015), Why does financial sector growth crowd out real economic growth?" BIS Working Paper No. 490.

Cerutti, Eugenio, Stijn Claessens, and Luc Laeven (2017), "The Use and Effectiveness of Macroprudential Policies," *Journal of Financial Stability,* 28: 203-224.

Cerutti, Eugenio, Ricardo Correa, Elisabetta Fiorentino, and Esther Segalla (2017), "Changes in Prudential Policy Instruments – A New Cross-Country Database," *International Journal of Central Banking* 13(1): 477-503.

Chinn, Menzie and Hiro Ito (2006), "What Matters for Financial Development? Capital Controls, Institutions, and Interactions," *Journal of Development Economics* 81(1): 163-192.

Cizel, Janko, Jon Frost, Aerdt Houben and Peter Wierts (2016), "Effective macroprudential policy: Cross-sector substitution from price and quantity measures," IMF Working Paper No. 16/94.

Claessens, Stijn and Enrico Perotti (2007), "Finance and Inequality: Channels and Evidence," *Journal of Comparative Economics* 35: 748-773.

Cournède, Boris, Olivier Denk and Peter Hoeller (2015), "Finance and Inclusive Growth," OECD Economic Policy Paper No. 14.

Dabla-Norris, Era, Kolpana Kochhar, Nujin Suphaphiphat, Frantisek Ricka and Evridiki Tsounta (2015), "Causes and Consequences of Income Inequality : A Global Perspective," IMF Staff Discussion Note No. 15/13.

De Haan, Jakob and Jan-Egbert Sturm (2015), "Income Inequality, Capitalism, and Ethno-Linguistic Fractionalization," *American Economic Review* 105(5).

--- (2016), "Finance and Income Inequality: A Review and New Evidence," CESifo Working Paper No. 6079.

Demirgüç-Kunt, Asli and Ross Levine (2009), "Finance and Inequality: Theory and Evidence," *Annual Review of Financial Economics* 1(1): 287-318.

Drehmann, Mathias and Kostas Tsatsaronis (2014), "The Credit-to-GDP Gap and Countercyclical Capital Buffers: Questions and Answers," BIS Quarterly Review.

Fernández, Andrés, Michael W. Klein, Alessandro Rebucci, Martin Schindler, and Martín Uribe (2015), "Capital Control Measures: A New Dataset," IMF Working Paper No. 15/80.

Frost, Jon, and René van Stralen (2018), "Macroprudential policy and income inequality," *Journal of International Money and Finance,* 85(C): 278-290.

Furceri, Davide and Prakash Loungani (2015), "Capital Account Liberalization and Inequality," IMF Working Paper No. 15/243.

Galati, Gabriele and Richhild Moessner (2014), "What do we know about the Effects of Macroprudential Policy?" DNB Working Paper No. 440.

Galbraith, James K. and Jiaqing "Jack" Lu (1999), "Inequality and Financial Crises: Some Early Findings," in James K. Galbraith and Maureen Berner (eds.), *Inequality and Industrial Change: A Global View,* Cambridge: Cambridge University Press.

García-Herrero, Alicia, Alvaro Ortiz and David Martínez (2015), "Flourishing middle classes in the emerging world to keep driving reductions in global inequality," BBVA EAGLEs Economic Watch, 2 March.

Gennaioli, Nicola, Andrei Shleifer and Robert Vishny (2014), "Finance and the Preservation of Wealth," *Quarterly Journal of Economics* 129(3): 1221-1254.

Jaumotte, Florence, Subir Lall and Chris Papageorgiou (2013), "Rising Income Inequality: Technology, or Trade and Financial Globalization?" *IMF Economic Review* 61(2): 271-309.

Jorda, Oscar (2005), "Estimation and inference of Impulse Responses by Local Projections," *American Economic Review,* 95(1): 161-182.

López-Salido, David, Jeremy C. Stein and Egon Zakrajšek (2016), "Credit-Market Sentiment and the Business Cycle," NBER Working Paper No. 21879.

Jorgenson, Dale, and Khuong Vu (2013), "The Emergence of the New Economic Order," *Journal of Policy Modeling* 35(3): 389-399.

Kuznets, Simon (1955), "Economic Growth and Income Inequality," *American Economic Review* 45(1): 1-28.

Laeven, Luc and Fabián Valencia (2013), “Systemic Banking Crises Database,” *IMF Economic Review* 61(2): 225–270.

Lee, Jong-Eun (2006), “Inequality and Globalization in Europe,” *Journal of Policy Modeling* 28(7): 791-796.

Ostry, Jonathan D., Andrew Berg and Charalambos G. Tsangarides (2014), “Redistribution, Inequality, and Growth,” IMF Staff Discussion Note No. 14/02.

Philippon, Thomas (2015), “Has the US Finance Industry Become Less Efficient? On the Theory and Measurement of Financial Intermediation,” *American Economic Review* 105(4): 1408-38.

Piketty, Thomas (2014), *Capital in the Twenty-First Century*, Cambridge: Belknap Press.

Schmitt, John (2009), “Inequality as Policy: The United States Since 1979,” Center for Economic and Policy Research (CEPR) Reports and Issue Briefs, 2009-40.

Schularick, Moritz and Alan M. Taylor (2012), “Credit Booms Gone Bust: Monetary Policy, Leverage Cycles, and Financial Crises, 1870-2008,” *American Economic Review*, 102(2): 1029-61.

Solt, Frederick (2016), “The Standardized World Income Inequality Database,” *Social Science Quarterly*, 97(5): 1267-1281.

World Bank (2016), “Poverty and Shared Prosperity 2016: Taking on Inequality,” October.

World Bank (2016), “Global Financial Development Database (GFDD),” 2015/2016 version.

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