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

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Abstract

Does financial development increase income inequality? Ambiguous answers to this question may be due to over-aggregation of 'financial development'. In a sample of 40 developed economies over 1990-2013, we study the effects on income inequality of different components of financial development. There was a shift in bank credit allocation, away from supporting investments by non-financial firms and towards financing real estate markets ('debt shift'). In system-GMM estimations, we find that mortgage credit increases income inequality while credit to non-financial business reduces inequality. The effect of business credit is conditional on macroeconomic and labor market factors related to broader income formation, such as wage share, investment, trade openness, and labor force participation. House prices and the size of the real estate sector condition the impact of mortgage credit on income inequality.

Keywords: income inequality, financial development, debt shift

JEL: E51, G21, I30

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1 Introduction

The relationship between income inequality and the growth of the financial sector has been subject to increased scrutiny since the Global Financial Crisis (GFC). Income inequality has risen substantially in most OECD countries since the late 1980s (Atkinson, 2015; OECD, 2015; Milanovic, 2016). This is commonly attributed to factors outside the financial sector, notably skill-biased technological change, trade globalisation (Jaumotte et al., 2013; Dabla-Norris et al., 2015), labor market institutions (Card et al., 2004; Jaumotte and Buitron, 2015), and taxation (Agnello and Sousa, 2014). But it was precisely in the years of unprecedented financial sector expansion in most OECD countries that inequality increased so much (Greenwood and Scharfstein, 2013). Is there a connection? The question is important from both research and policy perspectives.

The traditional consensus in economics has been that financial development decreases income inequality, by enabling a larger share of the population to save, invest, manage risk and smooth consumption, resulting in more equitable wage distributions (Banerjee and Newman, 1993). Recent research (see Section 2 for a review) has pointed to other mechanisms, which might deliver a different outcome. A larger financial sector may inflate real estate and equity prices, generating rents and capital gains which translate into increased incomes for asset owners, more than for others. Increasing income inequality would be a possible outcome.

This scenario has been the subject of a policy debate, especially since the publication of Piketty (2014). The focus of this debate is not so much on the financial sector as on the role of capital in the economy. Piketty argues that income growth is increasingly linked to capital gains, interest, and dividends rather than to wages and entrepreneurship. This trend is a cause for concern if it increases economic inequality and undermines incentives for work and innovation. The financial sector plays a central role in this process, since it allocates financial resources over asset markets on the one hand, and productive and entrepreneurial activities on the other hand. The two cannot be neatly separated, but the large rise of bank lending to real estate markets in the form of household mortgages, and the simultaneous fall in the share of bank lending to non-financial business, has been widely documented (see e.g., Jorda et al., 2016). Across many countries, there was a shift in the allocation of bank credit – 'debt shift', for short (Bezemer et al., 2016). This debt shift may be part of the income-inequality increasing process identified by Piketty and others.

The aim of this paper is to address this question empirically. To the best of our knowledge, this has not been done before. We construct measures for the two largest components of financial development — credit to non-financial business and household mortgage credit — for 40 developed economies over the period 1990–2013. We analyze their impact on Gini coefficients of gross income inequality (pre-tax, pre-transfers). We account for endogeneity concerns stressed by Bazillier and Hericourt (2017) and Bazillier et al. (2017), by applying a system-GMM methodology.

We find that the commonly used total-credit measure of financial development has a significant positive impact on income inequality. Once we distinguish between the two types of credit, we observe opposite effects. Household mortgage credit increases income inequality, while credit to non-financial business decreases income inequality. The significance and direction of these effects have not changed after the GFC.

These results suggest that 'debt shift' may be one of the factors explaining recent trends in income inequality. Credit to real estate asset markets results in rising capital gains and growth of incomes connected to the real estate sector. Since these incomes are concentrated among rich households, this widens income disparities. In support, we find that mortgage credit increases the income share of households in the top 10% of the income distribution.

Examining factors that may condition the effect of credit on income inequality, we observe that in economies where real house prices are low and real estate sectors are large in terms of their value-added shares, the scope for mortgage credit to increase inequality is larger. We also find that the inequality-reducing effect of credit to non-financial business is smaller under macroeconomic and labor market conditions that already foster more equality – in economies with higher wage shares, non-residential investment, trade openness, and labor force participation.

The rest of the paper is organized as follows. Section 2 discusses how the shift in the allocation of bank credit may change the relation between financial development and income inequality. Sections 3 and 4 present the data and describe the methodology, respectively. Section 5 discusses the main results, while Section 6 offers robustness checks. Section 7 concludes with a summary and discussion of this paper's limitations and further work.

2 Debt Shift and the Finance-Inequality Nexus

The impact of financial development on inequality is theoretically ambiguous. Financial development may alleviate income inequality by easing credit constraints, stimulating human capital accumulation, reducing barriers to investment and increasing returns on investment (Galor and Zeira, 1993; Galor and Moav, 2004), as well as by providing more risk insurance opportunities (Greenwood and Jovanovic, 1990; Banerjee and Newman, 1993). This was empirically shown in studies for developing countries since the 1960s (Clarke et al., 2006; Beck et al., 2007; Claessens and Perotti, 2007). Beck et al. (2007, p.27) report that "financial development disproportionately boosts incomes of the poorest quintile and reduces income inequality." Measures other than credit volumes yield similar results. Mookerjee and Kalipioni (2010) find in a sample of developed and developing countries that greater access to bank branches reduces income inequality, while barriers to bank access significantly increase inequality.

Results for advanced economies are mixed.[1] Beck et al. (2007) report that financial development reduced inequality in the U.S. But Van Arnum and Naples (2013) find that the growth of the U.S. financial sector has contributed to the exacerbation of income inequality in recent decades. Likewise, Denk and Cournède (2015) report that financial expansion has held back income growth of low- and middle-income households in OECD economies. De Haan and Sturm (2017) find for a sample of 121 countries covering 1975-2005 that financial development increases income inequality. The

[1] See Demirgüc-Kunt and Levine (2009), Bazillier and Hericourt (2017), De Haan and Sturm (2017) for a survey of the literature on the relationship between financial development and inequality.

harmful effect of financial development on income distribution was also confirmed in other broader country samples (see e.g., Gimet and Lagoarde-Segot, 2011; Jaumotte et al., 2013; Li and Yu, 2014; Jauch and Watzka, 2016).

One reason for these mixed findings may be that 'total credit to the private sector' is often used as a proxy for financial development. The composition of the stock of bank credit has, however, changed dramatically in recent decades. Bezemer et al. (2016) find that the large rise in total bank credit in a balanced panel of 14 countries from 1990 to 2011 was mainly due to the growth in credit to real estate and financial asset markets, from 30% to 66% of GDP. In the same sample, bank credit to non-financial business was stable, increasing from 41% in 1995 to 46% of GDP in 2008. Similarly, Jorda et al. (2016) report an increase in household mortgage credit from 30% to 60% of GDP since 1900 in a sample of 17 countries, with most of this rise observed since the 1980s.

This shift in the composition (rather than only the level) of bank credit has so far not been considered in the finance-inequality literature. Yet it could matter for the understanding of channels from financial development to inequality. The traditional arguments for inequality-reducing effects of financial development include decreasing investment barriers and risk, with increasing opportunities for consumption smoothing. These arguments are relevant to non-financial business loans and consumer credit. Credit supporting investment and demand in the real sector has the potential to generate employment and higher wages and thereby a more equal income distribution. The strength of this effect will depend on labor market institutions, the economy's wage share, industrial structure, and the degree of trade openness. But given the right conditions in each of these areas, real-sector investment supported by domestic financial development can be a powerful income equalizer.

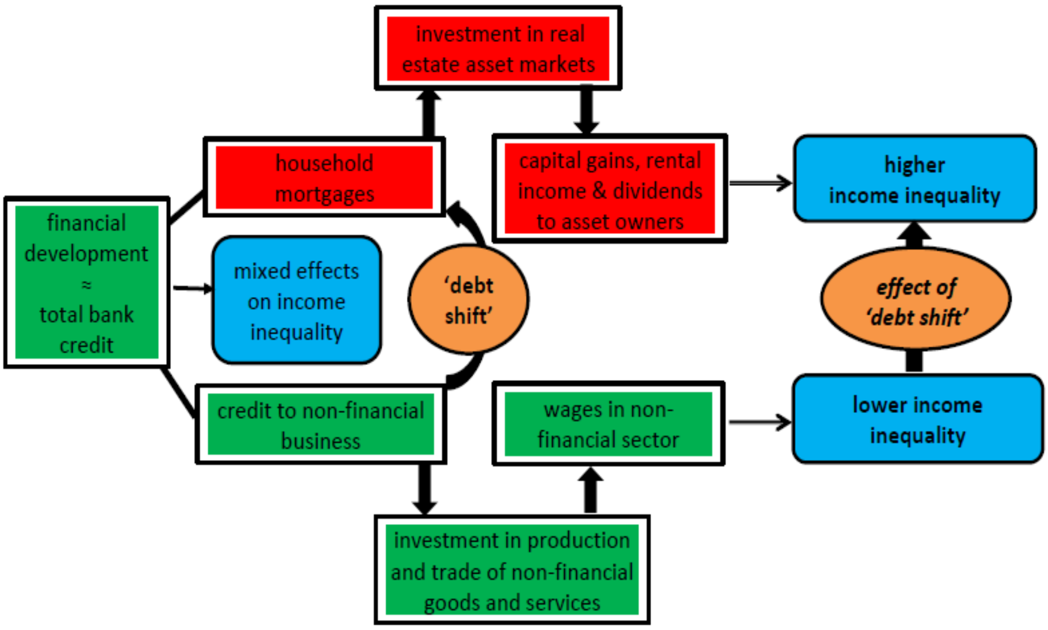
For credit to asset markets, another set of arguments comes into play, which rationalizes inequality-*increasing* effects of financial development. Piketty (2014) identifies redistribution between wage earners and owners of capital as a key reason for rising income inequality – where 'capital' includes real estate and financial assets. Bank credit to real estate markets in the form of mortgages drives up house prices (Favara and Imbs, 2015) and generates capital gains. These capital gains (and rising prices of financial products linked to real estate) will increase incomes in the forms of dividends, interest, rental incomes, and financial fees in the real estate sector, where incomes are typically already high and concentrated among the households at the top end of the income distribution.

There is some literature in support of this channel. Berisha et al. (2018) find for the U.S. data that the growth in the stock market and household debt increase income inequality. For the U.S., the U.K. and Germany most of the changes in income inequality are accounted for by changes in capital incomes, as Frässdorf et al. (2011) show. Kus (2012) examines variables related to capital gains (e.g. stock market valuations). Controlling for labor market institutions, unemployment, globalization and social spending, she reports a positive association of capital gains with income inequality for OECD economies over 1995–2007. Roine and Waldenström (2012) find that for Sweden, capital gains explain most of the inequality increase since the 1980s. Also, Von Ehrlich and Seidel (2015) show that increasing financial access for non-financial business reduces inequality between regions by spreading investment opportunities more equally over space. Therefore a shift of credit allocation away from businesses and towards mortgages is also likely to alter spatial income patterns in an inequality-increasing manner.

Depending on the extent of 'debt shift' (the shift in bank credit allocation from non-financial business towards household mortgages), the finance-inequality nexus could be either positive or negative. Underneath the effect of aggregate credit, the two credit categories we distinguish in this paper may have significant, but opposite effects on income inequality. Figure 1 illustrates debt shift and its impact on income inequality.

While there is no research to date linking debt shift to income inequality, our paper connects to a broader literature which shows that credit to non-financial firms has different effects than mortgage credit (Werner, 1997, 2012). Economies with higher household credit (most of which are mortgages) experience slower income growth (Jappelli et al., 2013; Büyükkarabacak and Valev, 2010; Beck et al., 2012; Bezemer et al., 2016;

Figure 1: Debt shift and its impact on income inequality



Jorda et al., 2016), larger external imbalances (Büyükkarabacak and Krause, 2009) and higher probabilities of crisis, with longer post-crisis recessions (Rose and Spiegel, 2011; IMF, 2012; Sutherland et al., 2012; Babecky et al., 2013). We add to this literature that growth in mortgages relative to business credit tends to increase income inequality.

3 Data

3.1 Data Description

We use annual data for 40 developed economies over 1990–2013, with the time period determined by data availability.[2] Gross income inequality is measured by the market Gini coefficient, taken from the Standardized World Income Inequality Database (SWIID). The Gini index gives a more general picture of inequality than top incomes measures as it takes into account the whole income distribution and not only dynamics at its extremes (Bazillier and Hericourt, 2017). We use the Gini market income measure (and not net income) as it is the most suitable proxy for income inequality before fiscal redistribution via taxes and transfers. In the robustness checks, we also consider gross

[2]The list of countries is provided in Table A.1 in Appendix.

labor earnings inequality and the top 10% gross income share. Table A.2 in Appendix describes the construction and data sources for income inequality measures.

The data for bank credit were collected from the consolidated balance sheets of Monetary Financial Institutions from central bank statistics of each country. We distinguish three types of domestic bank credit: credit to non-financial business, household consumption credit, and mortgages to households, all reported as percentages of GDP. The sum of the three credit types constitutes bank credit to the private non-financial sector. This is the total-credit proxy of financial development commonly used in the literature. A detailed description of the credit data set is provided in Bezemer et al. (2017).

Income distributions change relatively slowly, and therefore we do not use annual observations in the analysis but 3-year non-overlapping periods. Using annual time series data would also carry the risk of capturing short-term business cycles movements rather than the underlying finance-inequality relation.

In the benchmark analysis we include four control variables, which in previous studies were identified as important drivers of income inequality. These are: initial income levels, income growth, inflation, and unemployment.[3] Economic development and growth influence income inequality depending on the level of income and the distribution of growth over income levels (Dollar and Kraay, 2002; Huang et al., 2007). Inflation may lead to pressure for rising nominal wages, with that pressure unevenly distributed over different income groups, and depending on labor union strength (Kus, 2012). Higher inflation hurts low-income households who hold more currency and benefits high-income households with more capital (Easterly and Fischer, 2001; Albanesi, 2007). Rising unemployment hurts lower income groups who rely on labor earnings as their main income source. It also creates downward wage pressure for those employed, with additional effects on income distributions (Van Arnum and Naples, 2013). Table A.3 in Appendix provides details on the construction of

[3]In the robustness checks, we explored a wide range of other plausible covariates of income inequality, such as access to education, output gap, government expenditures, the economy's industrial structure, population growth, financial deregulation, economic globalisation, technological development, asset prices, and capital flows. Most of these were insignificant and did not affect our conclusions.

the control variables, and their data sources. Descriptive statistics and correlations are reported in Tables A.4 and A.5 in Appendix, respectively.

Any study on the finance-inequality nexus must consider reverse causality and endogeneity. Causality might run from inequality to financial development (Bazillier et al., 2017), or both may be caused by an unobserved third factor. For instance, larger household indebtedness and higher income inequality may be jointly caused by governments providing cheap credit to low-income households (Rajan, 2010). Inequality, once rising, may be self-reinforcing if it constrains effective demand (Carroll et al., 2017). Rising income inequality may cause poorer households to borrow more in order to sustain their consumption levels (Kumhof et al., 2015). There is evidence from the U.S. (where median incomes have long been stagnant but top incomes have raced away) for a 'keeping up with the Joneses' effect as a driving force in the growth of mortgage and consumer lending and increasing household indebtedness (Onaran et al., 2011; Coibion et al., 2014).

In response, previous studies (e.g., **?**Kunieda et al., 2014) instrument financial development with legal origin or other institutional factors. These cannot be used for disaggregated credit categories.[4] To deal with endogeneity, we employ a system-GMM estimator that uses internal instruments (see Section 4 for details).

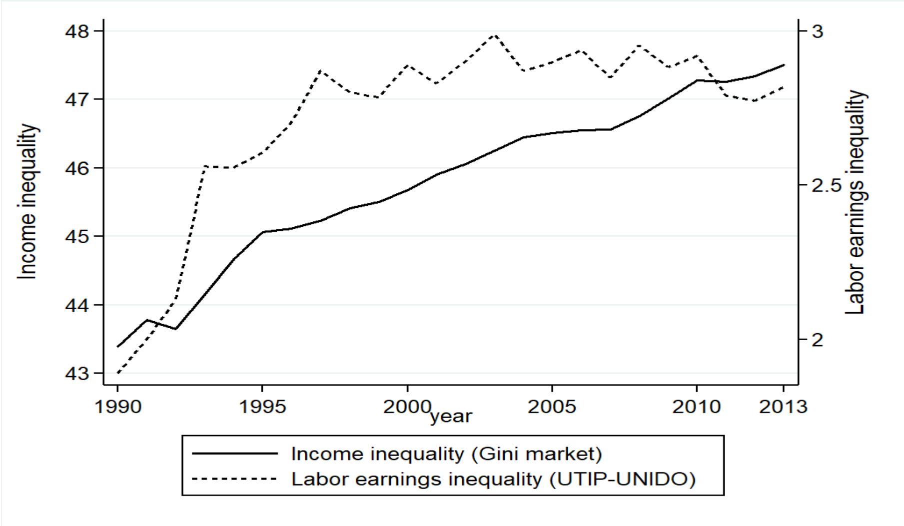
3.2 Trends in Income Inequality and Financial Development

Figure 2 shows the development of income and labor earnings inequality as the unweighted average in a balanced sample of 40 countries over 1990–2013. The Gini coefficient of gross income inequality increased steadily over time, from 43.4 in 1990 to 47.5 in 2013. Labor earnings inequality rose fast until the late 1990s and then stabilized.

Figure 3 presents trends in bank credit categories to the private non-financial sector over 1990–2013, as unweighted averages over an unbalanced panel of 40 countries. Although the unbalanced nature of the panel distorts trends somewhat, they are qual-

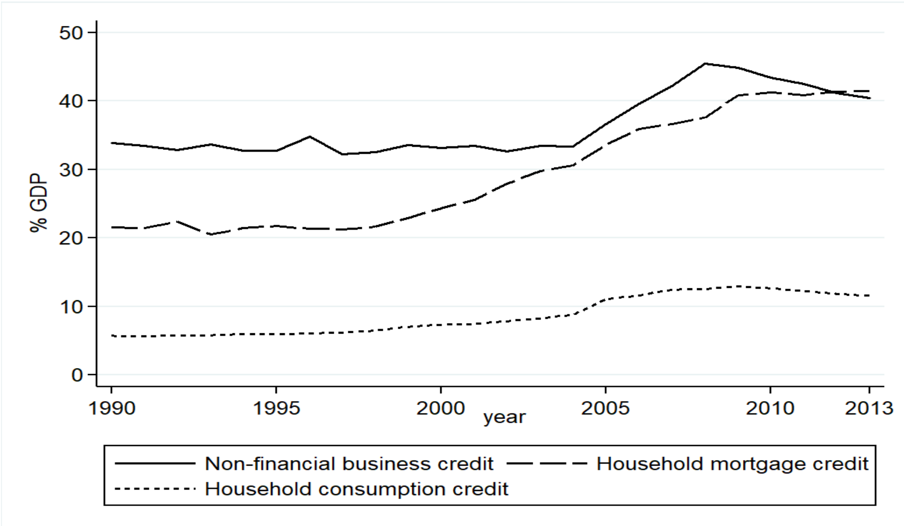
[4]Some studies use financial liberalization as an external instrument for total bank credit. It is unclear which of the two credit categories in our paper could be instrumented by financial liberalization.

Figure 2: Income and labor earnings inequality over 1990–2013



Sources: SWIID; University of Texas Inequality Project based on UNIDO Industrial Statistics.

Figure 3: Disaggregated bank credit over 1990–2013



Sources: central banks' statistics; authors' calculations.

itatively similar to those reported in Bezemer et al. (2016) and Jorda et al. (2016). We observe a strong increase in household mortgage credit, almost doubling from 22% to 41.5% of GDP on average from the late 1990s until 2013. Household consumer credit rises slightly from 6% in 1990 until 2005, then stabilizes just above 11%. Bank credit to non-financial business was stable as a share of GDP during 1990–2004 at around 33%, then rising to 45% in 2008 and subsequently falling back to 40% in 2013. Further exploration showed that this rise after 2004 is driven by eight countries in our sample (Bulgaria, Cyprus, Denmark, Estonia, Iceland, Ireland, Lithuania, and Spain). In

Table 1: Correlations of Gini coefficients with credit variables, 1990–2013

	Gini market
Total bank credit to private non-financial sector (1+2+3)	−0.11*
1. Non-financial business credit	−0.14**
2. Household consumption credit	0.04
3. Household mortgage credit	−0.09

Note: The table reports pairwise correlation coefficients between Gini coefficients of gross income inequality and credit stocks scaled by GDP. **p<0.05, *p<0.1.

contrast, the rise in mortgage credit is general.

In Table 1 we explore correlations over time and between countries of Gini coefficients and credit categories, based on 3-year periods over 1990–2013. The total stock of bank credit to the private non-financial sector is negatively correlated to the Gini coefficient of gross income inequality, with a correlation coefficient of -0.11. Credit to non-financial business has a slightly larger negative correlation coefficient of -0.14. Household mortgage and consumer credit have insignificant correlation coefficients with the Gini coefficient of -0.09 and +0.04, respectively. These explorations suggest that distinct credit categories differ in their associations with income inequality.

4 Methodology

We analyze the relationship between bank credit and income inequality in panel regressions, controlling for a number of covariates. Following the literature, we conduct the analysis using 3-year non-overlapping averages of annual data. This accounts for the low variability of income inequality and decreases the sensitivity of outcomes to short-term variations. The baseline model specification is the following:

$$INEQ_{it} = \alpha + \beta CRED_{it-1} + \gamma CTR_{it} + \mu_i + \lambda_t + \varepsilon_{it}, i = 1,..,N; t = 1,..,T, \qquad (1)$$

where $INEQ_{it}$ is the Gini coefficient of gross income inequality in country i and period t; $CRED_{it-1}$ is a matrix of bank credit to the private non-financial sector, including either total bank credit or one of the three categories of credit denoted *Business Credit*$_{it-1}$, *Mortgage Credit*$_{it-1}$ and *Consumer Credit*$_{it-1}$. Credit variables are included with a one-period lag. The three categories are defined as the stock of bank loans to non-financial business, to households as home mortgages, and to households as unsecured consumption credit, respectively, all scaled by nominal GDP. Further, β is a vector of estimated parameters for the credit variables. CTR_{it} is a matrix of control variables, described in Section 3.1. Finally μ_i are unobserved country-fixed effects; λ_t are time-fixed effects; and ε_{it} is an idiosyncratic error term with mean 0.

As noted, we face an endogeneity issue: rising income inequality might be driving an increase in credit (Bazillier et al., 2017). This means that $\mathbf{E}[CRED_{it-1}\varepsilon_{it}] \neq 0$. As a result, OLS inference methods (FE or RE estimators) will be biased and inconsistent. In order to deal with this endogeneity problem, we employ the system-GMM estimator for dynamic panel models, developed by Blundell and Bond (1998) (extending the work of Arellano and Bond (1991) and Arellano and Bover (1995)). This combines the equation (1) in levels with the equation (2) in first differences:

$$\Delta INEQ_{it} = \beta \Delta CRED_{it-1} + \gamma \Delta CTR_{it} + \Delta\lambda_t + \Delta\varepsilon_{it}. \qquad (2)$$

The endogenous variables $CRED_{it-1}$ are instrumented with their lags in the first-difference equation and by their first differences in the level equation.[5] We include second and further lags (2 .) and also lagged first-differences as instruments. To limit the number of instruments, we follow the approach of Roodman (2009) and collapse moment conditions by combining them into smaller sets.[6] As estimated asymptotic standard errors can be downward biased, we use Windmeijer (2005) two-step robust GMM for a finite-sample correction to standard errors.

System-GMM produces consistent and unbiased estimates, provided that the error terms ε_{it} in the baseline equation (1) are not serially correlated and that instruments, used to deal with endogenous regressors, are valid. We computed a Hansen J-test of over-identifying restrictions to check for the joint validity of instruments. We also test for the first- and second-order autocorrelation of residuals. The test results suggest

[5] We do not consider difference-GMM as it has poor finite sample properties, leading to low precision and coefficient bias, especially when series are persistent (Blundell and Bond, 1998). The system-GMM is a more efficient estimator as it uses also instruments in the level equation which are good predictors for endogenous variables.

[6] We use the Stata program `xtabond2` of Roodman (2006) to estimate system-GMM.

that the instruments are valid and strong.[7]

5 Estimation Results

Table 2 reports the estimation results based on our benchmark specification. As control variables we include those most widely used in the literature: initial income level (in the beginning of each 3-year period), income growth, inflation, and unemployment.[8] We find that higher income growth, higher inflation, and lower unemployment – all connected to a business cycle upswing – are associated with lower income inequality.

Controlling for these factors, we observe in column (1) that wider availability and uptake of bank credit to the private non-financial sector significantly increase the Gini coefficient. In column (2) we turn to the separate effects of credit aggregates. We find that *Business Credit* is significantly (at 5% level) associated with lower income inequality, while *Mortgage Credit* correlates positively and significantly (at 1% level) to the Gini coefficient. The coefficient estimate for *Consumer Credit* does not enter the model significantly, probably due to its small values. In our sample, the share of household consumer credit accounts on average for only 12% of all bank credit to the private non-financial sector.

In column (3) we drop *Consumer Credit* given its insignificance. The coefficient estimates for the two remaining credit categories rise in absolute value and in statistical significance. Their magnitudes are similar and they imply substantial effects in opposite directions. A one percentage point rise in credit to non-financial business as a share of GDP is associated with a decline of the Gini coefficient by 0.071. For household mortgage credit, the associated *rise* of the Gini coefficient is 0.079. In our sample of 40 countries, mortgage credit as a share of GDP rose on average from 23.2% to

[7] We note that GMM methods for panel data are designed for situations with "small T, large N". Our panel dataset has T=8 and N=40, which means that the cross-sectional dimension is rather small. However, keeping its limitations in mind, this is the best method available given our data. An alternative is to estimate the instrumental-variable model by GMM techniques, which uses only the level equation. However, it reduces the sample size substantially when including lagged regressors as instruments. Given this drawback, we do not consider such a method in our analysis.

[8] Many other variables could be argued to affect income inequality. In Section 6 we discuss the estimation results with additional control variables. Most of them are insignificant and would not affect the outcomes presented here, had they been included in the regression.

Table 2: Main estimation results: bank credit and income inequality

	(1)	(2)	(3)	(4)	(5)
Total bank credit	0.036 ***				
	(0.010)				
Business Credit		−0.045 **	−0.071 ***	−0.108 ***	−0.060 ***
		(0.020)	(0.023)	(0.022)	(0.017)
Mortgage Credit		0.057 ***	0.079 ***	0.079 ***	0.182 ***
		(0.021)	(0.024)	(0.015)	(0.062)
Consumer Credit		0.021			
		(0.065)			
Business Credit^2				0.0002 **	
				(0.0001)	
Mortgage Credit^2					−0.001 ***
					(0.0001)
GDP per capita	−0.948	−0.765	−0.679	−0.676	−1.106 *
	(0.787)	(0.923)	(1.335)	(0.960)	(0.638)
Income growth	0.041	−0.097 *	−0.150 **	−0.174 ***	−0.158 ***
	(0.046)	(0.055)	(0.070)	(0.031)	(0.058)
Unemployment	0.213 ***	0.222 ***	0.260 ***	0.252 ***	0.291 ***
	(0.048)	(0.050)	(0.059)	(0.049)	(0.055)
Inflation	−0.017 ***	−0.015 ***	−0.015 ***	−0.014 ***	−0.012 ***
	(0.003)	(0.003)	(0.004)	(0.003)	(0.002)
Observations	204	204	204	204	204
Countries	40	40	40	40	40
Hansen test p-value	0.143	0.376	0.382	0.973	0.347
AR(1) test p-value	0.009	0.009	0.049	0.033	0.047
AR(2) test p-value	0.242	0.819	0.991	0.913	0.758

Notes: The Table reports system-GMM estimates with Windmeijer (2005) two-step robust GMM standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Constant, time- and country-fixed effects are included in the estimations (not shown). AR(1) and AR(2) are the Arellano-Bond tests for first- and second-order serial correlation of residuals, respectively. The Hansen test p-value reports the Hansen over-identification statistic. The dependent variable is Gini market coefficient.

41.5% of GDP over 1990–2013. Based on the estimates in column (3), this implies a rise in the Gini coefficient by 1.45 (ceteris paribus). This is roughly one third of the average change in the Gini coefficient over the sample period. The effect of non-financial business credit is much smaller – its increase over 1990–2013 by 6.6% of GDP implies a drop in the Gini coefficient by 0.47 (ceteris paribus).

In sum, these baseline results offer empirical support for the differentiation in the effects of bank credit on income inequality that we proposed in Section 2. The finding of large impacts on inequality of the two main credit components, and their opposite signs, is the key contribution of this paper.

The relation between financial development and income inequality may be humpshaped (Greenwood and Jovanovic, 1990). That is, at low levels of financial development, more credit may increase inequality since not all benefit from it; but as more people gain access to finance, this helps to smooth the income distribution (Kim and Lin, 2011). To examine this, we add quadratic terms of credit categories, reported in columns (4) and (5) in Table 2.

The nonlinear effects are significant for both credit categories. *Mortgage Credit* increases the Gini coefficient, with this effect diminishing as credit grows. The total effect is positive for *Mortgage Credit* below 57% of GDP, which comprises about 86% of the sample. Note that the turning points in the credit-inequality relations implied by these estimates lie at very high values of credit, which are rarely observed in the sample. The effect of mortgage credit on income inequality is significantly negative above 73% of GDP. This holds only for 7% of all observations, from four countries: Denmark, the Netherlands, New Zealand, and Switzerland. For *Business Credit*, the total effect on income inequality remains significant and negative for the whole sample, even at very high levels of *Business Credit*. The quadratic term is negligible in magnitude.

5.1 Conditioning factors

So far, we tested a reduced form of the causal chain depicted in Figure 1. We now explore this causal sequence by examining possible factors that could condition the impact of different credit categories on income inequality.

First, larger real estate sectors could amplify the effect of mortgage credit on income inequality, via higher income growth in real estate-related sectors, relative to other sectors. As Rognlie (2015) shows, the recent increase in the share of aggregate income going to capital, observed in the U.S. and other advanced economies, is largely due to the housing sector. These capital incomes are linked to mortgage provisions, e.g. as interest spreads, fees and sales of related financial products and services such as valuation and insurances. The income growth in these sectors benefits predominantly households in the upper tail of the income distribution. For a given change in the stock of mortgages, the potential for mortgage expansion to affect the income distribution is larger in economies where more of income is earned in the real estate-related sectors.

We do not have a direct measure for incomes in the real estate-related sectors relative to other sectors for all countries in the sample. As a proxy, we use the share of value-added realized in real estate activities in total value-added. We condition the effect of mortgage credit on income inequality, on real estate value-added shares by including their interaction term. Following Brambor et al. (2006), we use graphs to interpret the interaction effects.

Column (1) in Table 3 shows that the higher the value-added share of the real estate sector, the larger is the impact of *Mortgage Credit* on income inequality. This is consistent with a role for incomes in the real estate-related sectors in mediating between mortgage expansion and income inequality. Figure 4(a) illustrates this in the positive slope of the marginal effects plot. The total effect is significant (on 10% level) for real-estate value-added shares equal to or larger than 12.5% of total value-added, accounting for 20% of all observations.

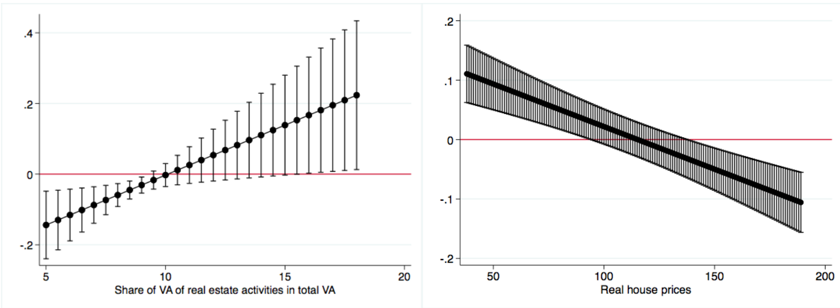
Table 3: Effects of *Mortgage Credit* conditional on value-added of real estate sector and on house prices

	(1)	(2)
Business Credit	−0.135 ***	−0.102 ***
	(0.017)	(0.027)
Mortgage Credit	−0.285 ***	0.165 ***
	(0.107)	(0.033)
Value-added share of real estate sector	−0.731 *	
	(0.409)	
Mortgage Credit×Value-added share of real estate sector	0.028 **	
	(0.012)	
Real house prices		0.054 ***
		(0.012)
Mortgage Credit×Real house prices		−0.001 ***
		(0.0003)
Observations	203	184
Countries	40	40
Hansen test p-value	0.680	0.920
AR(1) test p-value	0.559	0.936
AR(2) test p-value	0.692	0.847

Notes: The Table reports system-GMM estimates with Windmeijer (2005) two-step robust GMM standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Control variables, constant, time- and country-fixed effects are all included in the estimations (but not shown). AR(1) and AR(2) are the Arellano-Bond tests for first- and second-order serial correlation of residuals, respectively. The Hansen test p-value reports the Hansen over-identification statistic. The dependent variable is the Gini market coefficient.

Figure 4: Marginal effects of *Mortgage Credit* on income inequality conditional on value-added share of real estate sector and on house prices

(a) (b)



Notes: Solid lines show marginal effects of *Mortgage Credit* on Gini market coefficient at different levels of value-added share of real estate sector or real house prices; vertical boundaries indicate 95% confidence interval. The marginal effects are significant when solid lines and confidence intervals are above (below) zero.

Following the same reasoning, the impact of mortgage credit on income inequality may also vary with real estate prices. The effects of housing booms and busts on labor market incomes is documented (see e.g., Bonhomme and Hospido, 2017). As higher house prices primarily boost income and wealth of households at the upper tail of the distribution, they might amplify the effect of mortgage credit on inequality. We test for this mediating factor by including an interaction term of the real house price index with *Mortgage Credit*. We find a negative coefficient for the interaction term in column (2) of Table 3, which indicates that for higher values of the real house price index, the scope of mortgage credit to increase income inequality diminishes. This is perhaps because mortgages and house prices act as substitutes rather than complements in affecting inequality. Figure 4(b) illustrates this effect in the negative slope of the marginal effects plot. The Figure shows that taking the house price effect into account, the impact of mortgage credit on income inequality is still positive. The total effect of *Mortgage Credit* is positive and significant when the real house price index is below 98, which holds for 80% of all observations.

Next, we examine factors that condition the impact of *Business Credit* on income inequality. In Figure 1 we hypothesized that more bank credit to non-financial business loosens financing constraints on productive investment and leads to growth in wages which benefits low- and middle-income households more, and consequently reduces income inequality. However, in economies which already foster more equality through favorable macroeconomic and labor conditions leading to more employment and/or higher wages, the additional effect of non-financial business credit may be limited. Previous studies argue that more (public) investment and trade openness alleviate economic inequality (Dabla-Norris et al., 2015; Stiglitz, 2015). Also labor market institutions such as higher union membership, labor mobility, and labor force participation have income equalizing effects (Slottje et al., 1992; Agénor, 2004; Farber et al., 2018). We examine these conditional factors by including in the model three macroeconomic variables (wage share, non-residential investment, and trade openness, all as % of GDP) and two labor market variables (labor union strength and labor force participation) plus their interaction terms with *Business Credit*.

Table 4: Effects of *Business Credit* conditional on macroeconomic and labor market factors

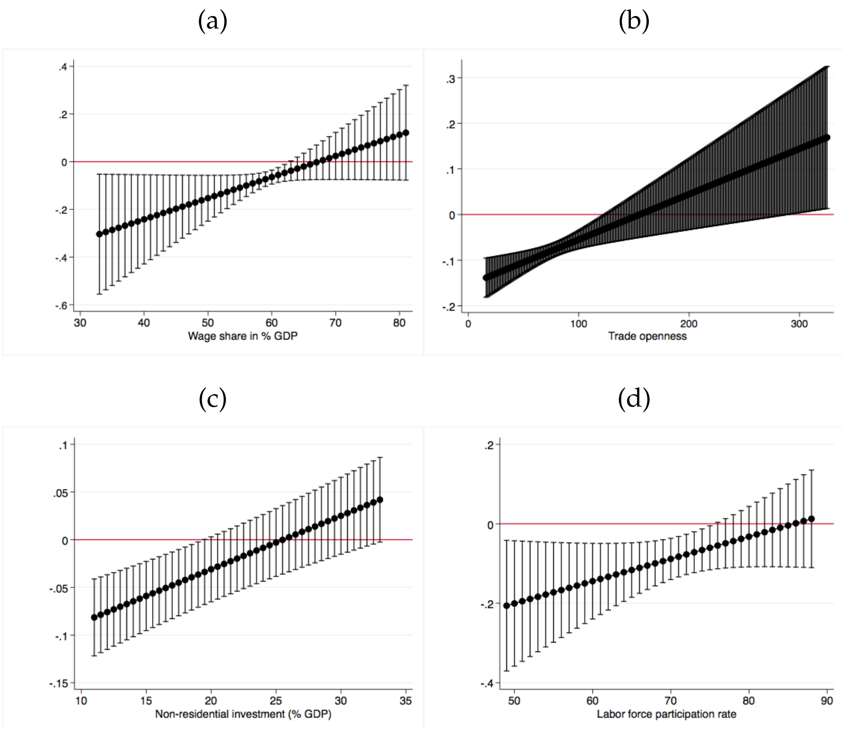
	(1)	(2)	(3)	(4)	(5)
Business Credit	−0.596 **	−0.155 ***	−0.143 ***	−0.198 **	−0.481 **
	(0.285)	(0.027)	(0.029)	(0.090)	(0.253)
Wage share	−0.420 **				
	(0.205)				
Business Credit×Wage share	0.009 *				
	(0.005)				
Trade openness		−0.042 ***			
		(0.011)			
Business Credit×Trade openness		0.001 ***			
		(0.0001)			
Non-residential investment			−0.445 ***		
			(0.100)		
Business Credit×Non-resid. investment			0.006 ***		
			(0.001)		
Labor union strength				−0.072	
				(0.048)	
Business Credit×Labor union strength				0.002	
				(0.001)	
Labor force participation					−0.309 *
					(0.177)
Business Credit×Labor force particip.					0.006 *
					(0.004)
Mortgage Credit	0.089 ***	0.044 **	0.045 ***	0.081 **	0.070 **
	(0.032)	(0.017)	(0.017)	(0.036)	(0.035)
Observations	201	204	201	185	201
Countries	40	40	40	36	40
Hansen test p-value	0.634	0.599	0.481	0.791	0.798
AR(1) test p-value	0.149	0.097	0.015	0.040	0.016
AR(2) test p-value	0.732	0.930	0.271	0.123	0.139

Notes: The Table reports system-GMM estimates with Windmeijer (2005) two-step robust GMM standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Control variables, constant, time- and country-fixed effects are all included in the estimations (but not shown). AR(1) and AR(2) are the Arellano-Bond tests for first- and second-order serial correlation of residuals, respectively. The Hansen test p-value reports the Hansen over-identification statistic. The dependent variable is the Gini market coefficient.

Table 4 shows the interaction effects as well as the variables included separately. The total effect of *Business Credit* on income inequality (taking into account the coefficient estimates for credit itself plus the interaction terms) becomes smaller in absolute value over higher wage shares, investment rates, trade openness, and labor force participation rates. This suggests that if macroeconomic and labor market conditions are more income-equalizing, the additional effect of bank credit to non-financial business is smaller.

Note that the coefficient for *Business Credit*, while increasing with values for each of these variables, is still negative for most of the sample. We illustrate this in the margins plots in Figure 5. When interacted with wage shares, non-residential investment, trade openness, and labor force participation, the respective total effects of *Business Credit* on income inequality are negative for 95%, 74%, 86%, and 75% of all observations.

Figure 5: Marginal effect of *Business Credit* on income inequality conditional on macroeconomic and labor market factors



Notes: Solid lines show marginal effects of *Business Credit* on Gini coefficient at different levels of wage share, trade openness, non-residential investment, or labor market participation; vertical boundaries indicate 95% confidence interval. The marginal effects are significant when solid lines and confidence intervals are above (below) zero.

6 Robustness Checks

We conduct an extensive sensitivity analysis to examine the robustness of our results to post-GFC years, alternative inequality measures, inclusion of additional variables, extreme values, and single countries. For reasons of space we do not report all these results in tables; they are available on request.

First, we test whether the main findings are robust to controlling for the Great Recession years. In order to examine whether the relation between credit categories and income inequality has changed after the GFC, we construct a dummy variable that takes a value 1 for years 2008-2013, and 0 otherwise. We interact this dummy with credit variables as analyzed in Table 2 (total, business, and mortgage credit). The results in columns (1)-(2) of Table A.6 in Appendix show that the coefficient estimates for all credit types are statistically significant with same signs as in Table 2. The interaction terms with the post-GFC dummy are mostly insignificant. This suggests that the relationship between credit categories and income inequality has not been different in the post-GFC period as compared to the pre-GFC period.

Second, we use alternative income inequality measures. Capital gains and capital income are an important part of the transmission mechanisms explored in this paper, and it would be useful to understand if they drive the results. We therefore replace gross total income inequality measured by the Gini coefficient with gross labor earnings inequality proxied by the Thei index (see Table A.2. in Appendix for a description). This excludes income dispersion arising from other income sources than wages, such as capital incomes and transfers. Table A.6, columns (4), in Appendix shows that using this inequality measure does not change our main conclusions.

We then explore sensitivity to top incomes. Incomes linked to mortgage expansion – whether directly in real estate sectors, or indirectly via rising prices of houses and financial products linked to real estate – are likely to be disproportionately concentrated among top income earners. We therefore re-run the analysis using the top 10% income share as the dependent variable.[9] We re-estimated our models with total bank credit

[9] Since the World Income and Wealth Database (`http://wid.world/data/`) has 1% and 10% top in-

and with the two credit categories. Table A.6, columns (5)-(6), in Appendix shows that the impacts on the top 10% income share of total or business credit are insignificant. This may be due to the smaller sample, but it is plausible that changes in business credit have little impact on the income of households at the top end of the income distribution. In contrast, as expected, more mortgage credit significantly increases the income share of top 10% of households, widening the income dispersion.

Third, we considered additional control variables that might be driving income inequality. These are: output gap, value-added share of manufacturing, average years of schooling, government expenditures, population growth, financial deregulation, economic (trade and financial) globalisation, technological development, capital inflows, and stock prices.[10] Adding all these variables simultaneously to the already instrumentally overloaded system-GMM estimator would result in too many instruments, leading to low power of specification tests. We include them one by one in separate regressions. All results for credit categories are qualitatively similar to the benchmark; most of additional controls enter with insignificant coefficients. It is noteworthy that higher shares of manufacturing value-added and more deregulated financial markets correlate significantly with lower income inequality. Economic globalisation plays a role too – higher index of financial globalisation and higher capita inflows are associated with higher Gini coefficients, while higher index of trade globalisation is associated with lower Gini coefficients.

Finally, we explore the sensitivity of the results to extreme credit values or single countries. We excluded the highest and lowest 5% of observations for household mortgages and non-financial business credit. We conclude that the results are not driven by these extreme values. Then we re-estimated the models while dropping each country consecutively, one by one, from the sample. Also this did not alter the main outcomes: the sample-average results are not driven by single countries.

come share data for only 22 countries in our sample, we use instead the data from World Bank World Development Indicators, which report top 10% income shares from 2004 onwards for all countries.

[10]See Table A.3 in Appendix for details on the construction and data sources of the control variables.

7 Conclusion

The empirical evidence on the relationship between financial development and income inequality is mixed and inconclusive. Our contribution is to disaggregate bank credit to the private non-financial sector into its two main components: household mortgage credit and credit to non-financial business, as well as household consumer credit, which is a much smaller credit component. We explore arguments why credit to non-financial business, which supports investment, demand, employment and wages, would decrease income inequality; and why mortgage credit, which supports real estate capital gains and incomes in the real estate sector, would increase inequality.

We use data on disaggregate bank credit over 1990–2013 for 40 developed economies and employ the system-GMM to estimate their effects on Gini coefficients of gross income inequality. The results indicate opposite effects of the two main credit aggregates, which are economically and statistically significant. A one percentage point rise in credit to non-financial business as a share of GDP is associated with a decline in the Gini coefficient by 0.071. For household mortgage credit, the associated *rise* of the Gini coefficient is 0.079. There appear to be nonlinear effects, but only above large values of credit-to-GDP ratios which are relevant to a small part of the sample.

We explore conditioning factors of the credit-inequality relation. The effect of non-financial business credit is conditional on macroeconomic and labor market factors related to broader income formation, such as wage shares, investment, trade openness, and labor force participation. In addition, house prices and the size of the real estate sector condition the impact of mortgage credit on income inequality.

We find that the key results are not driven by the sample period, inequality measure used, inclusion of additional variables, extreme values, and single countries.

Overall, in this paper we go beyond a search for 'the' relation between financial development and income inequality. There are several effects in opposite directions, depending on the kind of financial development. Financial development in the form of expansion of mortgage credit – which was dominant over the last decades – tends to increase income inequality, but financial development as expansion of credit to business does not. This disaggregation is one way to separate effects running through asset markets from effects running through goods and services markets. Similar reasoning would suggest other disaggregation, data allowing. For instance, a substantial portion of credit to non-financial business is not necessarily financing output growth and wage formation, but commercial real estate, mergers and takeovers, or share buyback programs. These uses of credit will affect inequality (and other outcomes) through different channels, perhaps more akin to the capital-gain channels that seem to be relevant to household mortgage credit. The results in this paper demonstrate that with more detailed credit data, our understanding of the finance-inequality nexus can be improved.

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APPENDIX

Table A.1: Countries included in the analysis

Australia	Finland	Korea	Portugal
Austria	France	Latvia	Romania
Belgium	Germany	Lithuania	Slovakia
Bulgaria	Greece	Luxembourg	Slovenia
Canada	Hungary	Malta	Spain
Chile	Iceland	Mexico	Sweden
Cyprus	Ireland	Netherlands	Switzerland
Czech Rep	Israel	New Zealand	Turkey
Denmark	Italy	Norway	UK
Estonia	Japan	Poland	U.S.

Table A.2: Income inequality measures: description and data sources

Variable	Description	Sources
Income inequality	Gini coefficient of gross income inequality (pre-tax, pre-transfers). Measured as the area between the Lorenz curve and the equality diagonal. A Lorenz curve plots the cumulative percentages of total income received against the cumulative number of recipients, starting with the poorest. Gini coefficient ranges from 0 (perfect equality) to 100 (perfect inequality). Gini coefficients are constructed from several sources, with data collected by Luxembourg Income Study (LIS) used as standard. Gini coefficients are calculated on the basis of 11 combinations of welfare definition (market income, net income, or expenditure) and income equivalence scale (household per capita, household adult equivalent, household unadjusted, or person). The final series are standardized on the LIS household-adult-equivalent income data. For details, see Solt (2016).	SWIID
Labor earnings inequality	Gross wage inequality, defined as dispersion of wages (person equivalent) in manufacturing. It is measured by the between-group components of Theil's T statistics calculated across industries, based on the UNIDO Industrial Statistics. UNIDO's measures are comparable and consistent across countries, as they are based on 2 or 3 digit code of the International Standard Industrial Classification. For details, see Galbraith and Kum (2002).	UTIP
Top 10% income share	Percentage share of gross income that accrues to households in the top 10% of income distribution.	WDI WB

Table A.3: Explanatory variables: description and data sources

Variable	Description	Sources
Financial development	1) total bank credit to private non-financial sector; 2) credit to non-financial business; 3) household consumption credit; 4) household mortgage credit. All credit variables in % of GDP.	Central banks' statistics
Income level	GDP per capita (ln), in 2010 U.S. dollars	WDI WB
Income growth	Annual growth rate of GDP per capita	WDI WB
Unemployment	Unemployed as a share of labor force (in %)	WDI WB
Inflation	Annual CPI inflation rate	WDI WB
Wage share	Wage share as % of GDP at current prices	AMECO, OECD
Non-residential investment	Non-residential investment (total gross fixed capital formation minus dwellings) in % GDP	AMECO, OECD
Trade openness	Sum of export and import of goods and services (% of GDP)	IFS IMF
Labor union strength	Trade union density, measured as the ratio of employees that are trade union members, divided by the total number of employees.	OECD
Labor force participation	Labor force divided by total working-age population (15-64)	OECD
VA share of RE	Share of Value Added of real estate activities in total Value Added of the economy (in %)	AMECO, OECD
Real house price	House price index (2010=100), deflated by CPI	OECD
Output gap	Gap between actual and potential GDP (% of potential GDP at constant prices)	AMECO, OECD
VA share of manufacturing	Share of Value Added of manufacturing in total Value Added (in %)	AMECO, OECD
Access to education	Average years of schooling for population aged >25	Barro and Lee (2013)
Government expenditure	General government final consumption expenditure (% of GDP)	WDI WB
Population growth	Annual growth rate (in %)	WDI WB
Financial deregulation	Credit market deregulation index. Includes 3 components: ownership of banks, extension of credit, and presence of interest rate controls/negative rates. The credit deregulation index is an average of the components; it takes values from 1 to 10.	Fraser Institute's Economic Freedom Indicators
Trade globalisation	De facto index, includes trade in goods, trade in services, and trade partner diversity	KOF, Gygli et al. (2019)
Financial globalisation	De facto index based on actual flows, includes foreign direct investment, portfolio investment, international debt, international reserves, and international income payments	KOF, Gygli et al. (2019)
Technological development	Share of ICT capital in total capital stock, in %. The data are available until 2010.	Jaumotte et al. (2013)
Capital inflows	Total gross inflows (% of GDP)	IMF BoP
Real stock price	Stock market index (2010=100), deflated by CPI	OECD

Table A.4: Descriptive statistics, 1990–2013 (3-year periods)

Variable	No obs.	Mean	Sd	Min	Max
Income inequality measures					
Gini market	317	45.78	5.27	29.12	60.27
Labor earnings inequality (×100)	298	2.73	1.97	0.29	11.00
Top 10% income share	186	26.40	5.02	20.43	46.15
Credit variables					
Bank credit to private non-financial sector (1+2+3)	244	78.66	42.30	8.60	249.87
1. Non-financial business credit	248	37.35	19.40	6.63	141.27
2. Household consumption credit	245	9.60	7.99	0.33	59.28
3. Household mortgage credit	245	31.50	26.53	0.13	133.15
Control variables					
GDP per capita (ln)	314	9.89	0.82	7.81	11.36
Income growth	311	2.03	2.80	−10.05	11.90
Unemployment	320	7.85	3.93	1.70	24.10
Inflation	315	10.84	36.12	−0.60	399.55
Wage share	308	54.17	7.04	33.16	81.02
Non-residential investment	306	18.31	4.01	10.04	33.29
Trade openness	316	85.72	48.01	16.23	348.68
Labor union strength	269	32.08	20.29	6.21	93.92
Labor force participation	294	70.39	7.06	49.82	87.47
VA share of RE	293	9.37	2.37	5.14	18.43
Real house price	248	89.24	25.74	38.61	189.29
Output gap	291	−0.45	2.66	−12.77	8.26
VA share of manufacturing	307	17.75	5.06	5.15	32.23
Years of schooling	317	10.57	1.66	4.82	13.58
Government expenditure	316	18.75	3.93	9.13	29.33
Population growth	320	0.53	0.83	−2.17	4.19
Financial deregulation	317	8.18	2.01	0.00	10.00
Trade globalisation	318	54.17	19.15	12.08	88.87
Financial globalisation	318	68.59	19.77	15.24	99.37
Technological development	266	4.68	3.37	0.11	18.44
Capital inflows	295	11.49	15.37	−76.40	91.77
Real stock price	242	100.24	47.08	15.50	316.68

Table A.5: Pairwise correlation coefficients for all variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1. Total credit (2+3+4)	1.00																						
2. *Business Credit*	0.79	1.00																					
3. *Mortgage Credit*	0.84	0.36	1.00																				
4. *Consumer Credit*	0.60	0.57	0.24	1.00																			
5. Ln GDP pc	0.61	0.35	0.63	0.28	1.00																		
6. Income growth	−0.41	−0.33	−0.34	−0.26	−0.27	1.00																	
7. Unemployment	−0.25	−0.13	−0.30	−0.02	−0.39	−0.01	1.00																
8. Inflation	−0.21	−0.14	−0.19	−0.16	−0.43	−0.16	0.19	1.00															
9. Wage share	0.33	0.19	0.34	0.10	0.29	−0.19	−0.19	0.03	1.00														
10. Non-resid. inv.	−0.19	−0.07	−0.17	−0.27	−0.35	0.41	−0.16	−0.03	0.01	1.00													
11. Trade openness	0.10	0.09	0.09	0.03	0.10	0.12	−0.05	−0.08	−0.20	0.04	1.00												
12. Labor union str.	0.26	0.26	0.11	0.30	0.37	−0.09	−0.09	0.02	0.04	−0.18	0.09	1.00											
13. Labor force part.	0.60	0.33	0.64	0.23	0.60	−0.20	−0.27	−0.22	0.22	−0.03	−0.08	0.35	1.00										
14. VA share RE	−0.04	−0.07	−0.03	0.05	0.15	−0.28	0.02	−0.02	−0.08	−0.30	−0.38	−0.08	0.10	1.00									
15. Real house price	0.19	0.27	0.08	0.06	−0.12	−0.05	−0.27	0.16	0.02	0.33	−0.01	−0.32	0.04	−0.02	1.00								
16. Output gap	0.02	0.05	−0.02	0.06	−0.02	0.40	−0.41	0.11	−0.02	0.26	0.02	−0.04	−0.02	−0.11	0.34	1.00							
17. VA share manuf.	−0.38	−0.22	−0.34	−0.34	−0.39	0.22	0.08	0.22	0.16	0.43	−0.07	0.02	−0.26	−0.27	0.02	0.04	1.00						
18. Schooling	0.29	0.13	0.33	0.20	0.39	−0.08	−0.14	−0.25	0.01	0.13	0.20	0.02	0.50	0.10	0.14	−0.03	−0.10	1.00					
19. Gov. expend.	0.20	0.24	0.06	0.28	0.24	−0.17	0.22	−0.11	−0.01	−0.26	0.06	0.55	0.35	0.06	−0.20	−0.12	−0.19	0.28	1.00				
20. Popul. growth	0.29	0.20	0.25	0.16	0.39	−0.12	−0.40	−0.18	0.02	−0.25	−0.02	0.07	0.03	0.16	−0.10	0.10	−0.33	−0.04	−0.19	1.00			
21. Financial dereg.	0.27	0.02	0.35	0.22	0.50	0.13	−0.18	−0.55	−0.14	−0.05	0.13	−0.11	0.23	0.20	−0.09	0.07	−0.31	0.35	−0.04	0.21	1.00		
22. Capital inflows	0.12	0.03	0.15	0.08	0.10	0.18	−0.16	−0.07	−0.07	−0.02	0.39	−0.04	−0.01	−0.18	0.06	0.33	−0.10	0.02	0.03	0.02	0.20	1.00	
23. Real stock price	0.04	0.08	−0.01	0.08	0.01	0.27	−0.14	−0.07	−0.14	0.04	0.12	−0.18	−0.09	0.06	0.40	0.44	0.01	0.11	−0.16	−0.04	0.17	0.35	1.00

Table A.6: Robustness checks: controlling for post-GFC years, alternative inequality measures

	Post-GFC effect		Labor earnings inequality		Top 10% income share	
	(1)	(2)	(3)	(4)	(5)	(6)
Total bank credit	0.043 ***		−0.004		−0.015	
	(0.013)		(0.006)		(0.020)	
Total bank credit×Post-GFC	−0.001					
	(0.006)					
Business Credit		−0.068 **		−0.023 ***		0.004
		(0.032)		(0.008)		(0.008)
Business Credit×Post-GFC		0.021				
		(0.037)				
Mortgage Credit		0.061 ***		0.013 **		0.039 **
		(0.020)		(0.007)		(0.019)
Mortgage Credit×Post-GFC		−0.007 *				
		(0.004)				
GDP per capita	−1.430 *	−0.351	−1.753 ***	−1.967 ***	−1.562	−3.200 ***
	(0.807)	(1.224)	(0.284)	(0.283)	(1.250)	(0.874)
Income growth	0.033	−0.133	−0.050 **	−0.061 ***	−0.235 *	−0.139 **
	(0.054)	(0.094)	(0.024)	(0.021)	(0.126)	(0.070)
Unemployment	0.211 ***	0.250 ***	−0.073 ***	−0.053 ***	−0.118	−0.148 *
	(0.051)	(0.075)	(0.027)	(0.020)	(0.124)	(0.087)
Inflation	−0.017 ***	−0.014 ***	−0.001	−0.001	0.077	0.038
	(0.003)	(0.004)	(0.001)	(0.001)	(0.117)	(0.072)
Observations	204	204	191	191	147	147
Countries	40	40	39	39	39	39
Hansen test p-value	0.309	0.303	0.281	0.525	0.109	0.199
AR(1) test p-value	0.016	0.013	0.075	0.075	0.347	0.527
AR(2) test p-value	0.202	0.980	0.141	0.209	0.235	0.102

Notes: The Table reports the estimates of system-GMM, with Windmeijer (2005) two-step robust GMM standard errors in parentheses. ***p<0.01, **p<0.05, *p<0.1. Constant, time- and country-fixed effects are included in the estimations (not shown). AR(1) and AR(2) are the Arellano-Bond tests for first- and second-order serial correlation of residuals, respectively. The Hansen test p-value reports the Hansen over-identification statistic.

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