Does Credit Composition Have Asymmetric Effects on Income Inequality?

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Abstract

This paper studies the effects of credit to private non-financial sectors on income inequality. In particular, we focus on the distinction between household and firm credit, and investigate whether these two types of credit have adverse effects on income inequality. Using balanced panel data for 30 developed and developing countries over the period of 1995-2013, we show that firm credit reduces income inequality whereas there is no significant impact of household credit on income inequality. We conclude that not the size of private credit but the composition of it matters for reducing income inequality due to the asymmetric effects of different types of credit.

JEL Classification: G20; D31; O16; D60

Keywords: *Household credit; firm credit; income inequality; credit composition; mean group estimator*

1. Introduction

The impact of financial development on economic growth has long been at the center of the theoretical and empirical finance literature. Although a vast literature emphasizes that financial development contributes to subsequent economic growth[1] by relaxing financial constraints that corrects capital misallocation and mitigates productivity losses, there is a paucity of research with respect to the finance-inequality nexus. Although it is known that income inequality has increased over the past quarter-century[2], the exact impact of financial development on income inequality has not been well defined in both empirical studies and the theoretical literature. The vast majority of the empirical finance-inequality studies find that financial development lead to less income inequality, suggesting more finance is good for the poor. [3] However, the literature has mainly focused on private credit, higher levels of which indicate more-developed financial systems and easier access to credit for entrepreneurs and households, while examining the linkages between financial development and income inequality (see, e.g., Clarke et al., 2006; Kappel, 2010; Beck et al., 2007; Law and Tan, 2009). Since these two types of borrowers, namely entrepreneurs and households, vary in terms of the use of credit, they might have different effects on the level of income inequality. Therefore, understanding whether firm credit,

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[1] Papers including Goldsmith (1969), McKinnon (1973), Shaw (1973), King and Levine (1993a), Bencivenga et al. (1995), Rousseau and Wachtel (2000), Beck and Levine (2004), and Demirguc-Kunt and Levine (2008) report positive association between financial development and economic growth. See Robinson (1952), Lucas (1988), Naceur and Ghazouani (2007), Harris (1997), and Cecchetti and Kharroubi (2012) for papers reporting negative or statistically insignificant association between financial development and economic growth. See Levine (2005) for comprehensive reviews of the related literature.

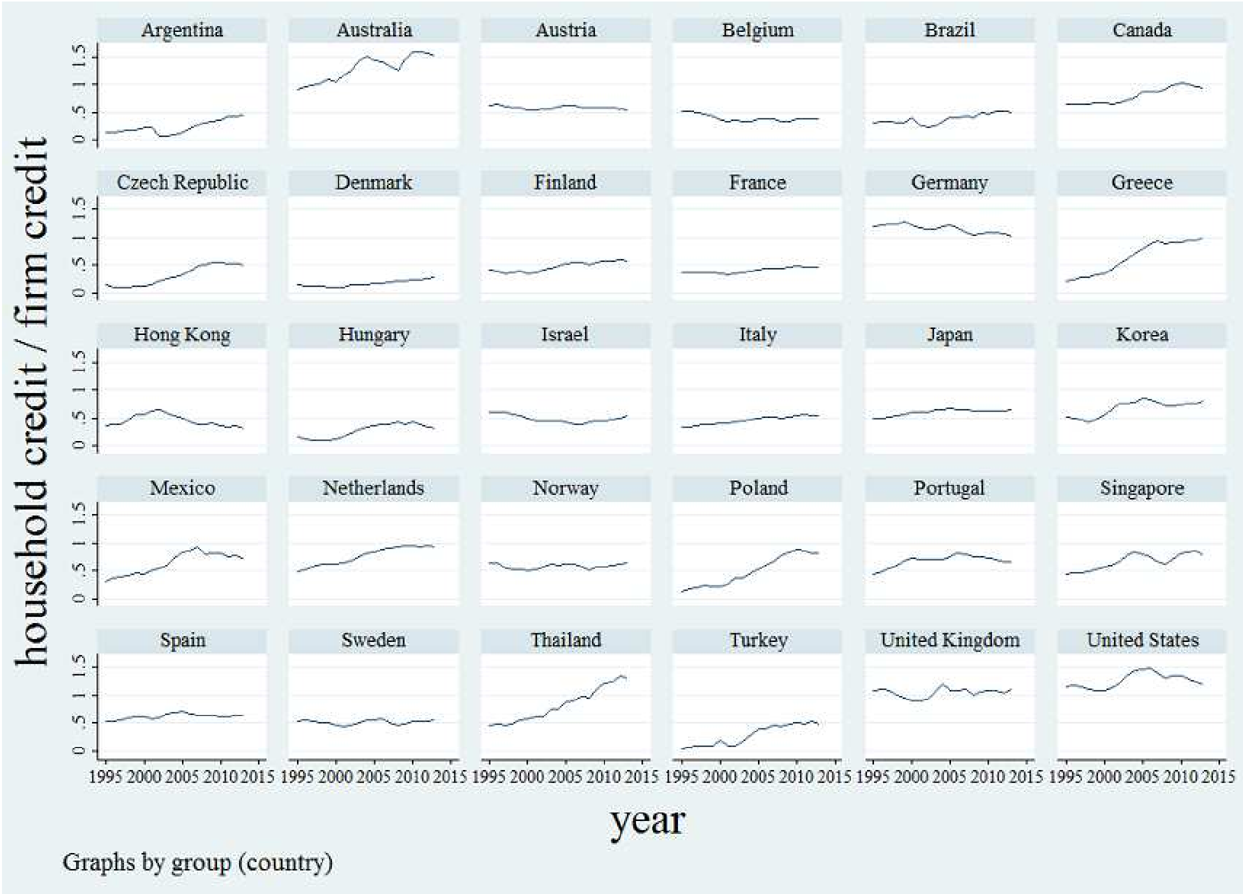
[2] While global inequality has declined mainly thanks to the development spurt of China and India, inequality within individual countries has worsened in a remarkably consistent fashion in both the developed and developing countries over the last three decades.

[3] Papers including Li, Squire and Zou (1998), Clarke et al. (2006), Beck et al. (2007), Dollar and Kraay (2002), Ravallion (2001), Kappel (2010), Uddin et al. (2014), and Abosedra et al. (2016) report negative relationship between financial development and income inequality, namely that financial development reduces income inequality. On the other hand, Charlton (2008), Law and Tan (2009), Jauch and Watzka (2015), and Seven and Coskun (2016) report negative or statistically insignificant relation between finance and income inequality/poverty. See Seven and Coskun (2016) for a broad review of the related literature.

household credit or both contribute to reducing income inequality can help policymakers who are interested in achieving a more equal income distribution.

In this paper, we study the link between the two components of private credit and income inequality. We argue that analyzing the separate effects of household and firm credit is more important for explaining the role of credit in income inequality than the size of total private credit per se due to two main reasons. *First*, theory points to different channels through which private credit can reduce income inequality. On the one hand, household credit enables the poor to invest in their human capital and health activities, hence reducing income inequality (Galor and Zeira, 1993; Banerjee and Newman, 1993). On the other hand, countries with higher levels of financial development might experience more efficient capital allocation across entrepreneurs (incumbent and new), higher economic growth and lower income inequality, an effect, which can be captured by firm credit (Gine and Townsend, 2004; Beck, Levine and Levkov, 2010; Beck et al., 2012; Dabla-Norris et al., 2015). In that aspect, understanding the exact mechanism of generating less income inequality through providing credit requires a more nuanced analysis. *Second*, the ratio of household credit to firm credit is above 0.5 for many developed and developing countries in our sample, and an increasing proportion of private credit has been given to the households rather than entrepreneurs over the last two decades (Figure 1). Since the proportion of household credit in total private credit has been substantially increasing and there have been increasing concerns both on the adverse effects of household debt burden and credit growth, especially in developing countries, focusing only on the size of private credit does not sit very well with reality. Therefore, exploring the decomposition of private credit becomes highly relevant for both economic growth and income inequality policies.

FIGURE 1. The Ratio of Household Credit to Firm Credit (Annual Data, 1995-2013)



Source: BIS, Authors' calculations.

In this respect, we extend finance-inequality literature by decomposing the effects of firm and household credit on income inequality. In particular, we differentiate between household credit and firm credit while the literature has mostly focused on the total credit to private sector. Therefore, this research contributes to the literature by identifying the heterogeneous behavior of income inequality (measured by GINI coefficient) in response to *(i)* credit to non-financial corporations (firm credit), and *(ii)* credit to households and non-profit institutions serving households (NPISHs) (household credit) across 30 developed and developing countries. Moreover, we contribute to the literature on the finance-inequality nexus also by estimating the effect of total credit to private non-financial sectors (total private credit), a common measure of financial development, on income inequality. The empirical analysis is based on balanced panel data including annual observations for 30 selected countries over the period between 1995 and 2013. To that end, the Common Correlated Effects Mean Group (CCEMG) estimator proposed by Pesaran (2006), and Augmented Mean Group (AMG) estimator proposed by Eberhardt and Bond (2009) are employed. Contrary to the existing literature, these methods take into account the cross-sectional dependence that may arise from economic integration of countries and/or common financial, political and social shocks, and provide both the common and the country-specific estimations. We also include trade openness, foreign direct investment inward stock, government final consumption expenditure, and corruption index as control variables, which are selected from the related literature and expected to affect income inequality. We show that the response of income inequality to credit to non-financial corporations is significant and negative, whereas credit to households and NPISHs is insignificant. Moreover, the effect of total private credit on income inequality is negative but statistically insignificant. These results suggest that the composition of funds between households and firms has key implications for policies to tackle income inequality. When these two types of credit have different effects on the level of income inequality, the composition becomes even more important. This is because when policymakers are confronted with the need to restrict (or expand) credit growth, they should pay particular attention to the asymmetric effects that household and firm credit have on income inequality. Hence, the composition of credit can support policymakers by enabling them to understand whether, and in which context private credit is an instrument that can influence income inequality, and whether the size of the total credit is always good for the poor.

Our study is further related to both the empirical and theoretical studies on the distinction between household and firm credit, all of which show that the composition of private credit matters for different macroeconomic variables. For example, Japelli and Pagano (1994) find that an increase in household credit decreases saving rates for a sample of OECD countries. Büyükkarabacak and Krause (2009) suggest that the composition of credit does matter for the trade balance such that lending to consumers has a negative effect on net exports, while firm loans contribute to a rise in net exports. Moreover, Bahadir and Gumus (2016), using a two-sector real business cycle model of a small open economy, analyze the differential effects of household and business credit dynamics on business cycles in emerging market economies. Their results suggest that the two types of credit shocks generate different dynamics in sectoral input and output levels as well as the real exchange rate.

Although there is a bunch of research distinguishes between the components of private credit, to the best of our knowledge, the only empirical research on the finance-inequality nexus that distinguishes between household and firm credit is Beck et al., (2012). Their paper examines the differential effects of household and enterprise credit on economic growth, income inequality and poverty. The authors find negative relation between enterprise credit and growth of Gini coefficient, but no statistically significant impact of household credit. However, Beck et al., (2012) use cross-country data (only 33 observations in their sample) for the period of 1992-2005. Moreover, they do not control for the cross sectional dependence. The distinguishing features of our paper are that we *(i)* provide both country-specific and panel estimates, *(ii)* take into account the cross-sectional dependence, *(iii)* use a comprehensive and updated data set, and *(iv)* employ cross-section augmented cointegrating regressions. Our findings are in line with the theoretical predictions of Gine and Townsend (2004) and Beck, Levine and Levkov (2010), those of which suggest that the impact of private credit on reducing income inequality goes through firm credit rather than household credit, and contradicting with theories focusing on credit for the poor helping them to exit poverty by investing in human capital, health and microenterprises activities (Galor and Zeira, 1993; Banerjee and Newman, 1993).

The plan of the paper is as follows. Section 2 describes our data and provides visual evidence for the hypothesis we test. Section 3 explains the details of the employed empirical strategy. Section 4 discusses and interprets the empirical results. Section 5 concludes.

2. Data Description

We combine country-level annual data gathered from five sources: the Standardized World Income Inequality Database (SWIID), the Bank for International Settlements (BIS) Statistics, the World Bank World Development Indicators, International Country Risk Guide (ICRG) Database, and United Nations Conference on Trade and Development (UNCTAD) Statistics. The sample consists of 30 developed and developing countries covering 19 consecutive years – i.e., the period 1995-2013.[4] The choices of country set and data period are shaped by data availability concerns. In particular, we focus on countries having no missing value for any of our selected variables over time.

Our analysis is based on three main variables: *(i)* Gini coefficient, *(ii)* credit to non-financial corporations (TCF), and *(iii)* credit to households and non-profit institutions serving households (TCH). The dependent variable is the market Gini coefficient, indicated by *GINIMARKET*, which is drawn from the Standardized World Income Inequality Database (SWIID) and constructed by Solt (2009) using the Luxembourg Income Study as the harmonized benchmark for comparable estimates. The SWIID is our preferred source of data on income inequality as it provides comparable figures across countries and over a longer span of time. The market Gini coefficient is calculated on income before taxes and transfers, and it measures inequality in income distribution without considering the effect of taxes and social spending

[4] The sample consist of Argentina, Australia, Austria, Belgium, Brazil, Canada, Czech Republic, Denmark, Finland, France, Germany, Greece, Hong Kong SAR, Hungary, Israel, Italy, Japan, Republic of Korea, Mexico, the Netherlands, Norway, Poland, Portugal, Singapore, Spain, Sweden, Thailand, Turkey, United Kingdom and the United States of America.

already in place in a country. We have also used the net Gini coefficient (after taxes and transfers), indicated by *GININET*.

Our main explanatory variables, credit to non-financial corporations and credit to households and NPISHs, which have been used interchangeably, are retrieved from the Bank for International Settlements (BIS) Statistics. It would be helpful briefly summarizing the content of the data to better understand the structure of the BIS data on private credit. The BIS has constructed long series on credit to the private non-financial sector for both advanced and emerging economies. Credit is provided by domestic banks, all other sectors of the economy and non-residents. The private non-financial sector includes non-financial corporations (both private-owned and public owned), households and non-profit institutions serving households. In terms of financial instruments, credit covers loans and debt securities. The data for each country include *(i)* credit to private non-financial sectors by domestic banks and *(ii)* total credit to private non-financial sectors. Moreover, total credit is broken down into *(iii)* credit to non-financial corporations and *(iv)* credit to households and non-profit institutions serving households. Hence, credit to non-financial corporations as a percentage of GDP and credit to households and non-profit institutions serving households as a percentage of GDP, both of which are in market values and adjusted for breaks, are used as explanatory variables in the analysis.

To assess the strength of the linkage between credit components and income inequality, we control other potential determinants of income inequality in the regressions. We use four control variables that are widely employed in the related literature. These variables are also introduced into the model as a test of robustness. First, we include the ratio of trade to GDP (*TRADE*) to capture the degree of openness of an economy. Second, the ratio government final consumption expenditure to GDP (*GGFCE*) is used to measure macroeconomic stability. Third, to measure the level of institutional quality we use corruption index (*CORR*), lower values of which indicate higher level of corruption (or lower institutional quality), hence, expecting that lower values of corruption index should be associated with a higher level of income inequality as it shows how corrupt the public sector is. Finally, we control for the foreign direct investment inward stock to GDP ratio (*FDI*). The source of data of *TRADE* and *GGFCE* is the World Bank DataBank. The data of *CORR* is compiled from International Country Risk Guide (ICRG) Database whereas the data of *FDI* are extracted from United Nations Conference on Trade and Development (UNCTAD) Statistics.

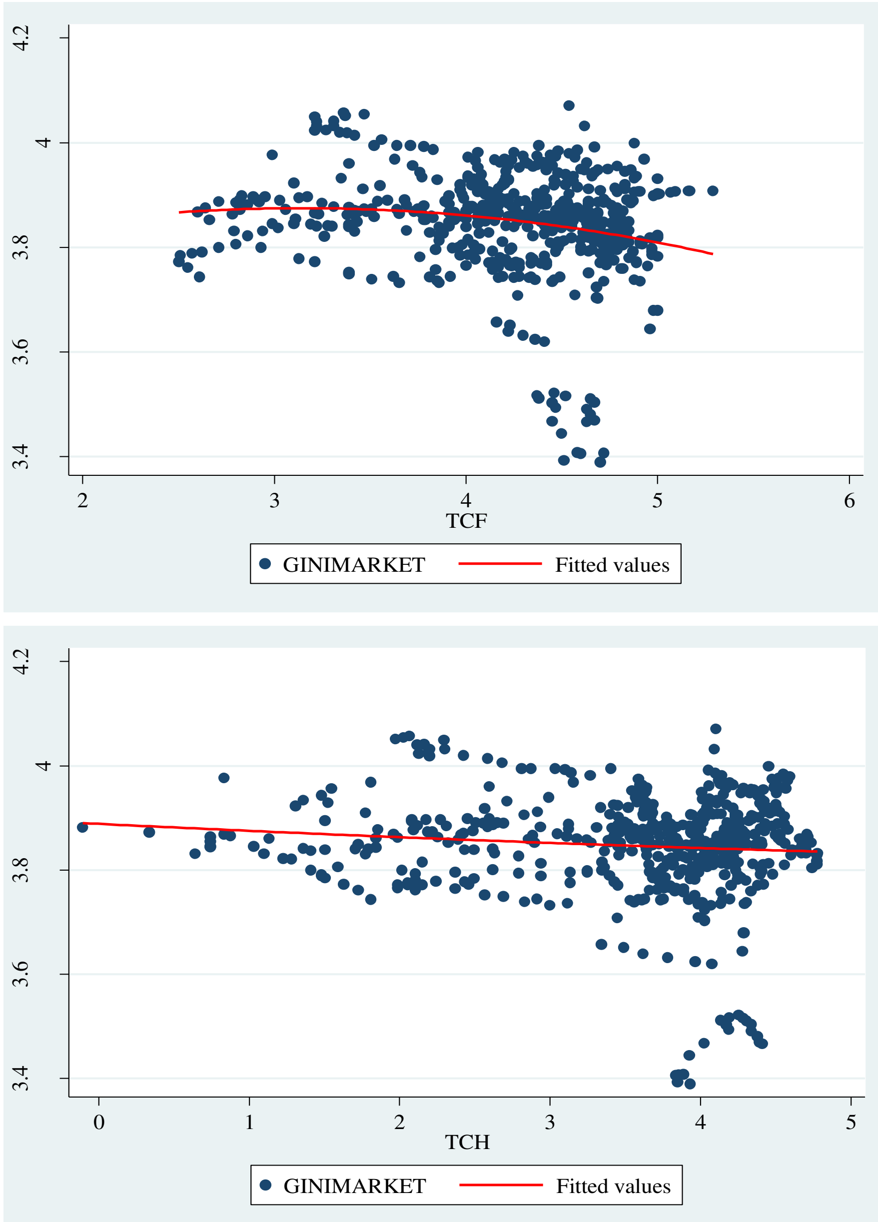
Table 1 presents the descriptive statistics for the variables used in our empirical analysis. There are considerable variations in our variables across countries. For example, the market Gini coefficient ranges from a low of 29.66% to 58.59%. Household credit to GDP and firm credit to GDP ratios also show significant variations, with TCH ranging from 0.9% to 118.8% and TCF from 12.2% to 197.5%. Figure 2 displays the visual evidence representing the raw correlations between our main explanatory variables (household and firm credit) and the dependent variable (the market Gini coefficient).

TABLE 1. Descriptive Statistics

Variables	Observations	Mean	Std. Dev.	Min.	Max.
GINIMARKET (%)	570	47.07	4.42	29.66	58.59
GININET(%)	570	32.94	7.37	21.58	55.50
TCF (% of GDP)	570	77.35	34.60	12.2	197.5
TCH (% of GDP)	570	47.04	27.98	0.9	118.8
CORR	570	3.88	1.29	1	6
GGFCE (% of GDP)	570	18.39	4.45	8.03	28.06
FDI (% of GDP)	570	44.05	66.72	0.63	542.49
TRADE (% of GDP)	570	89.26	80.38	15.64	455.28

Notes: Std. Dev., Min. and Max. denote standard deviation, minimum and maximum, respectively.

FIGURE 2. Visual evidence



Notes: The figures provide a visual representation of the unconditional relationship between firm credit to GDP ratio and the market Gini coefficient in the upper panel, and household credit to GDP ratio and the market Gini coefficient in the lower panel. All values are in natural logarithms.

3. Empirical Strategy

The goal is to develop an empirical strategy that would enable us to estimate the distinguished effects of household and firm credit on the level of income inequality given the country-level data set we have. While several alternative measures of income inequality can be used in the analysis, we prefer to focus on two measures of income inequality, which are also the measures most commonly used in the literature; market Gini coefficient (*GINIMARKET*) and net Gini coefficient (*GININET*).[5] The basic regression model that we aim to estimate can be expressed as follows:

$$\ln[INEQ_{i,t}] = \beta_0 + \beta_1 \ln[TC_{i,t}] + \boldsymbol{\beta}_2'(\boldsymbol{X}_{i,t}) + f_i + f_t + \epsilon_{i,t} \tag{1}$$

where i and t are country and time indices, $INEQ_{i,t}$ represents the income inequality measure, $TC_{i,t}$ represents, alternatively, credit to non-financial corporations (*TCF*) and credit to households and non-profit institutions serving households (*TCH*), $\boldsymbol{X}_{i,t}$ is the vector of control variables that include $CORR_{i,t}$, $\ln(GGFCE_{i,t})$, $\ln(FDI_{i,t})$ and $\ln(TRADE_{i,t})$, f_i and f_t denote country and time fixed effects, respectively, and $\epsilon_{i,t}$ is the usual error term. Finally, ln stands for the natural logarithm. Our main parameter of interest is β_1, which approximately describes the percentage point change in income inequality measures as a response to one percentage point increase, alternatively, in firm credit and household credit.

The growing body of literature claims that panel data sets tend to show cross-sectional dependence, which may arise from economic integration of countries, common shocks (such as financial, political and social shocks), and sometimes unobserved factors that eventually become the part of error (disturbance) term (Pesaran, 2004). Since traditional estimation methods have become inconsistent or inefficient in the presence of cross-sectional dependence, new techniques have been developed in panel data econometrics for stationarity and cointegration analysis and

[5] See Section 2 for detailed definitions of the variables used in the empirical analysis.

estimation procedure, which take account of cross-sectional dependence.[6] To resolve this potential problem, we consecutively employ i) Bias-Adjusted CD test developed by Pesaran et al. (2008), ii) cross-sectionally augmented Im-Pesaran-Shin (CIPS) panel unit root test proposed by Pesaran (2007), iii) the second generation panel cointegration tests of LM Bootstrap test of Westerlund and Edgerton (2007), and Durbin-Hausman test of Westerlund (2008), which allow for the dependence of cross-sectional units, and iv) Common Correlated Effects (CCE) estimator proposed by Pesaran (2006), Common Correlated Effects Mean Group (CCEMG), and Augmented Mean Group (AMG) estimator proposed by Eberhardt and Bond (2009), which allows for cross-sectional dependency arising from multiple unobserved common factors.[7]

4. Empirical Results

As testing for cross-sectional dependence in panel data is necessary to decide on the estimation method, the first step of the empirical analysis is cross-sectional dependence (CD) tests to analyze the contemporaneous correlation across countries in the panel.[8] *Panel A* and *Panel B* of Table 2 report the results of Bias-Adjusted CD test developed by Pesaran et al. (2008) for each series and for the models, respectively.[9] The results imply that for both the models with intercept

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[6] Assuming that cross-sectional dependence is due to common unobserved components, but that they are uncorrelated with the included regressors, the Fixed-Effects (FE) and Random-Effects (RE) estimators are consistent, although not efficient, and the estimated standard errors are biased. However, if the common unobserved components are correlated with the included regressors, the FE and RE estimators are inconsistent and biased. See De Hoyos and Sarafidis (2006).

[7] See Section 4 for detailed description and advantages of the employed models.

[8] Note that if the time dimension (T) is larger than the cross-sectional dimension (N) in a panel data set, CD_{LM1} test of Breusch and Pagan (1980) can be used to test for cross-sectional dependence. However, if N is larger than T in a panel, just as in this analysis (N=30, T=19), the CD_{LM1} test statistic does not attain desirable statistical properties as it shows considerable size distortions (Pesaran, 2004). We have utilized Bias-Adjusted CD test of Pesaran et al. (2008), since it exhibits a finite sample behavior, compared to CD_{LM2} and CD_{LM} tests of Pesaran (2004); it successfully controls the size while maintaining satisfactory power in a panel with exogenous regressors. Bias-Adjusted CD test is consistent even when CD_{LM2} and CD_{LM} tests are inconsistent.

[9] In *Models* 1, 2, 3 and 4, the dependent variable is *GINIMARKET*. The independent variable is *TCF* in *Models* 1 and 2; *Model* 2, in addition, includes control variables. The independent variable is *TCH* in *Models* 3 and 4; *Model* 4, in addition, includes control variables. *Models* 5, 6, 7 and 8 are for robustness check, and they pursue the same ordering, where dependent variable is *GININET*.

and the models with intercept and trend, the test statistics reject the null hypothesis of no cross-sectional dependence for all series and for the *Models* 1-8.

TABLE 2. Cross-sectional Dependence Tests Results

Panel A: For the Series	Model with intercept		Model with intercept&trend	
Variables	statistics	p-values	statistics	p-values
$\ln(GINIMARKET_{i,t})$	1.584	0.057	2.736	0.003
$\ln(GININET_{i,t})$	3.038	0.001	3.428	0.000
$\ln(TCF_{i,t})$	4.560	0.000	3.920	0.000
$\ln(TCH_{i,t})$	3.150	0.001	5.557	0.000
$CORR_{i,t}$	3.671	0.000	3.770	0.000
$\ln(GGFCE_{i,t})$	6.543	0.000	4.921	0.000
$\ln(FDI_{i,t})$	3.243	0.001	3.392	0.000
$\ln(TRADE_{i,t})$	3.137	0.001	2.656	0.004
Panel B: For the Models				
Model 1	29.416	0.000	27.327	0.000
Model 2	47.938	0.000	34.936	0.000
Model 3	32.241	0.000	34.127	0.000
Model 4	39.590	0.000	36.687	0.000
Model 5	30.446	0.000	22.617	0.000
Model 6	34.235	0.000	38.719	0.000
Model 7	31.506	0.000	26.324	0.000
Model 8	48.032	0.000	42.483	0.000

Notes: In *Models* 1, 2, 3 and 4, the dependent variable is *GINIMARKET*. The independent variable is *TCF* in *Models* 1 and 2; *Model* 2, in addition, includes control variables. The independent variable is *TCH* in *Models* 3 and 4; *Model* 4, in addition, includes control variables. *Models* 5, 6, 7 and 8 are for robustness check, and they pursue the same ordering, where dependent variable is *GININET*. Bias-Adjusted CD tests the null of zero correlations in the case of panel models with strictly exogenous regressors and normal errors. The null hypothesis the test is the absence of cross-sectional dependence.

Given the presence of cross-sectional dependence in the panel, the first generation unit root tests become invalid. Therefore, in order to analyze the stationarity features of the series, cross-sectionally augmented Im-Pesaran-Shin (CIPS) panel unit root test proposed by Pesaran (2007) is employed. The CIPS test statistics is the sample averages of the individual cross-sectionally augmented ADF (CADF) statistics. The results of CIPS test for the panel are presented in Table 3. The CIPS test results indicate the failure to reject the null hypothesis of the presence of unit root for all series for both the model with intercept and the model with intercept and trend. In other words, all series are found to be non-stationary processes for the panel.

TABLE 3. CIPS Panel Unit Root Test Results

Variables	Model with intercept statistics	Model with intercept & trend statistics
$\ln(GINIMARKET_{i,t})$	-1.9225	-1.6800
$\ln(GININET_{i,t})$	-1.9704	-2.4502
$\ln(TCF_{i,t})$	-1.3580	-1.2864
$\ln(TCH_{i,t})$	-1.9775	-2.3444
$CORR_{i,t}$	-1.909	-1.9185
$\ln(GGFCE_{i,t})$	-1.3851	-1.1518
$\ln(FDI_{i,t})$	-2.0568	-2.5438
$\ln(TRADE_{i,t})$	-1.9886	-2.3337

Notes: The null hypothesis of the test is the presence of unit root in panel data with cross-sectional dependence in the form of common factor dependence. The critical values from Pesaran (2007, p.280-281, Tables 2.b and 2.c for N=30, T=20) are -2.32 (1%), -2.15 (5%), -2.07 (10%) for model with intercept; -2.83 (1%), -2.67 (5%), -2.58 (10%) for model with intercept and trend.

After we confirm the non-stationarity of the variables for the panel, the subsequent step is to test for cointegration among the dependent variable and the regressors. Given the presence of cross-sectional dependence in the panel, the first generation panel cointegration tests also become invalid. Hence, the second generation panel cointegration tests are employed by allowing for the dependence of cross-sectional units. Particularly, LM Bootstrap test of Westerlund and Edgerton (2007), and Durbin-Hausman test of Westerlund (2008) are utilized to ensure the presence of cointegration in *Models* 1-8. *Panel A* and *Panel B* of Table 4 report the results of LM Bootstrap and Durbin-Hausman tests, respectively. There is a strong evidence of cointegration in *Models* 1-8, since LM Bootstrap test results indicate the failure to reject the null hypothesis of the presence of cointegration, and Durbin-Hausman test results reveal the rejection of the null hypothesis of no cointegration.

TABLE 4. Panel Cointegration Tests Results

	Panel A: LM Bootstrap Test		*Panel B: Durbin-Hausman Test*	
	Model with intercept	Model with intercept&trend	dh_group	dh_panel
Model 1	3.911 (0.113)	3.728 (0.132)	11.873 (0.000)	4.738 (0.000)
Model 2	36.611 (0.738)	67.484 (0.664)	2.985 (0.001)	7.015 (0.000)
Model 3	2.290 (0.277)	2.611 (0.432)	11.766(0.000)	15.665 (0.000)
Model 4	38.610 (0.609)	69.477 (0.909)	5.640 (0.000)	2.827 (0.002)
Model 5	3.593 (0.107)	3.234 (0.182)	16.443 (0.000)	1.406 (0.080)
Model 6	32.591 (0.958)	60.675 (0.870)	2.512 (0.006)	4.742 (0.000)
Model 7	1.574 (0.557)	1.582 (0.475)	7.718 (0.000)	3.691 (0.000)
Model 8	35.146 (0.774)	63.754 (0.929)	5.345 (0.000)	6.273 (0.000)

Notes: The test statistics with p-values in parentheses are presented for LM Bootstrap test and Durbin-Hausman test in *Panel A* and *Panel B*, respectively. In *Panel A,* the critical value (95%) is based on the bootstrapped distribution with 5000 bootstrap replications. The bootstrap critical values are proposed by Westerlund and Edgerton (2007). The null hypothesis of LM Bootstrap test is the presence of cointegration in *Models* 1-8. The asymptotic p-values for the test are not presented, since they are computed on the assumption of cross-sectional independence. In *Panel B,* the panel statistic, denoted by dh_panel, is obtained by summing n individual terms before multiplying them together, whereas group mean statistic, denoted by dh_group, is obtained by first multiplying the various terms and then summing. The null hypothesis of Durbin-Hausman test is the absence of cointegration in *Models* 1-8.

As we verify the presence of cointegration in our basic model, the long-run relationship in the panel regression model given in Equation (1) is further estimated by two methods for panel cointegration estimation. The cross-section augmented cointegrating regression for each country is estimated by Common Correlated Effects (CCE) estimator proposed by Pesaran (2006), and Augmented Mean Group (AMG) estimator proposed by Eberhardt and Bond (2009). The latter allows for cross-sectional dependency, which potentially arises from multiple unobserved common factors. The CCE estimation procedure is advantageous, since it enables augmenting the basic regression with cross-section averages of the dependent variable and the observed regressors as proxies for the unobserved common factors. The CCE estimation procedure is presented in Equation (2).

$$ln(INEQ_{i,t}) = \alpha_i + \gamma_i X_{i,t} + \zeta_1 \overline{ln(INEQ_{\iota,t})} + \zeta_2 \bar{X}_t + \vartheta_{i,t} \text{ for } i = 1, \dots, N \text{ and } t = 1, \dots, T \quad (2)$$

where the coefficients ζ_1 and ζ_2 represent the elasticity estimates of $ln(INEQ_{i,t})$ with respect to the cross-section averages of $ln(INEQ_{i,t})$ and the observed regressors, respectively. Accordingly, $ln(TCF_{i,t})$ [alternatively, $ln(TCH_{i,t})$] and $Z_{i,t}$ (in Equation 1) are contained in $X_{i,t}$, and ϑ_{it} denotes the error term. This procedure allows the individual countries to respond to common time effects differently as reflected by the country-specific coefficients on the cross-sectionally averaged variables. It also provides consistent estimates even when the observed regressors are correlated with the common factors. Using this procedure, the individual coefficients, γ_i, can be estimated in a panel framework. The Common Correlated Effects Mean Group (CCEMG) estimation is a simple average of the individual CCE estimations. The CCEMG estimation procedure is shown in Equations (3) and (4).

$$\hat{\gamma}_{CCEMG} = \sum_{i=1}^{N} CCE_i \,/N \tag{3}$$

$$SE(\hat{\gamma}_{CCEMG}) = \left[\sum_{i=1}^{N} \sigma\left(\hat{\gamma}_{CCE_i}\right)\right]/\sqrt{N} \tag{4}$$

where $\hat{\gamma}_{CCEMG}$ and $SE(\hat{\gamma}_{CCEMG})$ are the estimated CCEMG coefficients and their standard deviations, respectively.

On the other hand, the AMG estimator regards time series data properties as well as the differences in the impact of observables and unobservables across panel groups. This estimator takes account the cross-sectional dependence through the involvement of a *'common dynamic effect'* in the country regression, which is extracted from the year dummy coefficients (D_t) of a pooled regression in first differences (FD-OLS), and represents the levels-equivalent mean evolvement of unobserved common factors across all countries (Eberhardt and Bond, 2009). Provided that the unobserved common factors compose part of the country-specific cointegrating relation, the augmented country regression model embraces the cointegrating relationship that is allowed to differ across countries. In this regard, it coincides with the assumption of CCEMG estimator (Pedroni, 2007; Eberhardt and Bond, 2009).[10] The first stage stands for a standard FD-OLS regression with *T-1* year dummies in first differences, from which the year dummy coefficients, relabeled as $\hat{\mu}_t^{\circ}$, are collected. In the second stage, this variable is included in each of the N standard country regressions. Then, the AMG estimations are derived as averages of the individual country estimations. The first and the second stages of AMG estimation procedure are shown in Equations (5) and (6), respectively.

$$\text{AMG – Stage (i)} \qquad \Delta \ln(INEQ_{i,t}) \ = \beta' \Delta X_{i,t} + \textstyle\sum_{t=2}^{T} c_t \Delta D_t + e_{it} \tag{5}$$

$$\Rightarrow \hat{c}_t = \hat{\mu}_t^{\circ}$$

$$\text{AMG – Stage (ii)} \qquad \ln(INEQ_{i,t}) = \varphi_i + \beta_i' X_{i,t} + c_i t + d_i \hat{\mu}_t^{\circ} + e_{it} \tag{6}$$

$$\hat{\beta}_{AMG} = N^{-1} \sum_{i} \hat{\beta}_i$$

where φ_i is constant, and e_{it} denotes the error term of stage (i) and stage (ii). $\hat{\beta}_{AMG}$ stands for cross-sectional group-specific AMG estimations which are averaged across the panel.

We start discussing our estimates with Table 5, which presents the results of the regression of log market Gini coefficient on log firm credit to GDP ratio (in columns 1, 2, 5, and 6) and log household credit to GDP ratio (in columns 3, 4, 7, and 8) - along with the controls. The regressions show that there is a statistically significant relation between firm credit to GDP ratio and the market Gini coefficient, suggesting countries with higher level of firm credit to GDP ratio

[10] Eberhardt and Bond (2009) compare the performance of AMG and CCEMG estimators through Monte Carlo simulations, and find robust results for both approaches.

experience lower income inequality. The results hold for both the CCEMG and AMG estimates. On the other hand, both the CCEMG and AMG estimates do not suggest a statistically meaningful correlation between household credit to GDP ratio and the market Gini coefficient. Among the control variables, only government expenditure to GDP ratio and trade to GDP ratio have statistically significant relation with the level of income inequality, where both have positive effects on the level of income inequality. These evidences imply that higher government spending and degree of openness of an economy may increase income inequality.

TABLE 5. Mean Group Type Estimations (the market Gini Coefficient and Credit Compositions)

Dependent Variable: ln($GINIMARKET_{i,t}$)								
Variables	**CCEMG**				**AMG**			
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
ln($TCF_{i,t}$)	-0.113 (0.036)***	-0.050 (0.028)*			-0.090 (0.027)***	-0.063 (0.267)**		
ln($TCH_{i,t}$)			0.057 (0.070)	-0.051 (0.041)			0.069 (0.050)	0.041 (0.042)
$CORR_{it}$		0.001 (0.006)		-0.001 (0.004)		-0.002 (0.007)		0.000 (0.007)
ln($GGFCE_{i,t}$)		0.190 (0.078)**		-0.041 (0.055)		0.190 (0.094)**		0.135 (0.100)
ln($FDI_{i,t}$)		-0.002 (0.009)		-0.008 (0.010)		-0.011 (0.009)		0.002 (0.008)
ln($TRADE_{i,t}$)		0.054 (0.071)		-0.055 (0.050)		0.044 (0.025)*		0.042 (0.029)

Notes: The superscripts ***, **and * denote the statistical significance at 1%, 5% and 10% levels, respectively. Asymptotic standard errors are in parentheses.

In addition to the regressions with credit components, in Table 6, we present the results of the regression of log market Gini coefficient on total credit to private non-financial sectors as a percentage of GDP, which is the sum of household credit to GDP ratio and firm credit to GDP ratio, as defined in Section 2. This regression is estimated in order to examine the effect of total private credit on the level of income inequality to be able to compare our results with the existing literature on the finance-inequality nexus. Both the CCEMG and AMG estimates suggest a statistically insignificant relation between total credit to private non-financial sectors and the market Gini coefficient, though the relationship is negative. The estimates confirm our hypothesis that the composition of total private credit is more important than its size in reducing income inequality.

TABLE 6. Mean Group Type Estimations (the market Gini Coefficient and Total Private Credit)

Dependent Variable: $\ln(GINIMARKET_{i,t})$		
Variables	**CCEMG**	**AMG**
$\ln(TC_{i,t})$	-0.038 (0.038)	-0.049 (0.033)
$CORR_{it}$	-0.0002 (0.006)	-0.0003 (0.007)
$\ln(GGFCE_{i,t})$	0.122 (0.072)*	0.146 (0.064)**
$\ln(FDI_{i,t})$	-0.005 (0.008)	-0.014 (0.009)
$\ln(TRADE_{i,t})$	0.005 (0.061)	0.044 (0.030)

Notes: The superscripts ***, **and * denote the statistical significance at 1%, 5% and 10% levels, respectively. Asymptotic standard errors are in parentheses.

We also explore the relation between credit components and the net Gini coefficient (GININET). The nature of analysis is same as the one executed in Table 5. Similar to Table 5, the CCEMG and AMG estimates suggest a negative and statistically significant relation between firm credit to GDP ratio and the net Gini coefficient, while the relationship is statistically insignificant for household credit to GDP ratio.[11]

In addition to the panel estimates, the cross-section augmented cointegrating regression for each country is also estimated by CCE and AMG estimators. Table 7 presents the signs of the coefficients regarding the regressions between *(i)* firm credit and income inequality, and *(ii)* household credit and income inequality, using CCE and AMG estimators, respectively. The results show that though household credit is negatively and significantly associated with the market Gini coefficient in some countries (e.g., Greece, Israel, Poland and Spain), it increases income inequality in most of the countries (e.g., Belgium, Canada, Denmark, Hong Kong,

[11] All stationary, unit-root, panel cointegration, and long-run relationship tests are employed for the regressions between credit components and the net Gini coefficient. We do not present all results here in order to conserve space, but available upon request from the authors.

Hungary, Sweden). On the other hand, the relationship between firm credit and the market Gini coefficient is weak but negative in most of the countries. However these evidences should be interpreted with caution due to data constraints in the sample countries, we may suggest that country level credit decomposition-inequality analysis may enrich the empirical literature.

TABLE 7. Country-specific Regressions (summary of the Sign of the Coefficients)

Dependent Variable: ln($GINIMARKET_{i,t}$)				
Country	**CCE**		**AMG**	
	TCF	TCH	TCF	TCH
Argentina	+	+	+	-
Australia	+	-	+	-
Austria	(-) *	-	+	-
Belgium	-	(+) ***	-	(+) ***
Brazil	-	(-) ***	+	(+) ***
Canada	-	(+) ***	+	(+) ***
Czech Republic	-	-	-	-
Denmark	-	(+) ***	(-) **	-
Finland	+	-	+	+
France	-	-	-	+
Germany	(+) ***	-	(+) **	+
Greece	-	+	-	(-) ***
Hong Kong	(+) *	(+) **	(-) **	+
Hungary	+	-	+	(+) ***
Israel	-	(-) ***	+	-
Italy	-	-	-	-
Japan	+	-	-	+
Republic of Korea	-	-	(-) ***	+
Mexico	+	-	-	-
Netherlands	-	-	(-) **	+
Norway	+	(-) **	-	+
Poland	-	(-) ***	(-) ***	(-) ***
Portugal	-	-	-	-
Singapore	-	+	-	-
Spain	-	(-) ***	(-) ***	(-) ***
Sweden	-	+	+	(+) **
Thailand	+	+	+	+
Turkey	+	-	+	(-) *
United Kingdom	(-) **	+	-	(-) ***
United States	-	-	(-) ***	(-) ***

Notes: The superscripts ***, **and * denote the statistical significance at 1%, 5% and 10% levels, respectively.

5. Concluding Remarks

There are numerous studies investigating the link between financial development and economic growth. However, there is a scarcity of research on the relation between finance and income inequality, most of which focuses on the size of total credit given to the private sector. Although private credit is vital for the real economy, the ratio of household credit to firm credit is above 0.5 in many developed and developing countries in our sample, and an increasing proportion of private credit has been given to the households rather than entrepreneurs over the last two decades. Since these two types of borrowers, namely households and entrepreneurs, vary in terms of the use of credit, they might have different effects on the level of income inequality. Therefore, the main purpose of this paper is to specifically focus on the distinction between household and firm credit, and investigate whether these two types of credit have asymmetric effects on income inequality in a sample of 30 developed and developing countries over the period 1995-2013. In addition, we test the impact of total credit to private non-financial sectors to GDP ratio on the level of income inequality in order to motivate our main hypothesis that not the size of private credit but the composition of it matters for reducing income inequality. Our analysis also pays special attention to cross-sectional dependence issues, which are mostly ignored by the existing literature, and aims to present robust estimates on the role of credit components in reducing income inequality.

Our main finding is that firm credit reduces income inequality whereas there is no significant impact of household credit on the level of income inequality. This suggests that countries with low levels of firm credit in the non-financial sectors can experience lower income inequality by implementing policies encouraging firm credit expansion. On the other hand, countries with relatively high levels of household credit should implement policies discouraging household credit expansion, and encouraging firm credit expansion, taking into account the issue of over-expansion of private credit. We also find that total credit to private non-financial sectors is negatively but insignificantly associated with the market Gini coefficient, suggesting that there is no statistically significant effect of total credit on income inequality. Our results also suggest that while government consumption expenditure to GDP ratio and trade openness have positive associations with the level of income inequality, there is no statistically significant impact of either corruption index or foreign direct investment to GDP ratio on income inequality.

We conclude that not the size of private credit but the composition of it matters for reducing income inequality, and more credit may not always be good for the poor. Since household and firm credit have different effects on the level of income inequality, the composition of private credit becomes even more important. This makes policymakers to pay particular attention to the asymmetric effects that household and firm credit have on income inequality when they are establishing sector-specific credit policy.

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