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Original
Financial development and income distribution inequality in the euro area / Baiardi, Donatella; Morana, Claudio. - In: ECONOMIC MODELLING. - ISSN 0264-9993. - 70:(2018), pp. 40-55.

Availability:
This version is available at: 11381/2851218 since: 2021-11-10T00:15:50Z

Publisher:
Elsevier B.V.

Published
DOI:

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15 January 2025

Financial development and income distribution inequality in the euro area*

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July 2017

Abstract

The paper yields new evidence on real income convergence for euro area (EA) countries since the mid-1980s, with a special focus on the effects of the subprime and sovereign debt financial crises. By conditioning the turning point per capita income of the Kuznets curve (KC) to the level of financial development, we find strong evidence in favor of an EA-wide *steady-state financial KC* and of ongoing convergence across EA members toward a common per capita income turning point level. By means of a counterfactual analysis, we also point to worsening economic and income inequality conditions for all the EA countries, only partially ensued from "austerity" policies. Hence, a well-functioning financial system and its smooth development appear to be instrumental not only to economic growth, but also to a more egalitarian income distribution.

Keywords: Euro area; financial development; financial stability; income distribution inequality; Kuznets curve; real convergence; subprime mortgage and sovereign debt crisis.

JEL classification: G20, G28, O11, O15, O16.

*This project has received funding from the European Union's Seventh Framework Programme for research, technological development and demonstration under grant agreement no. 3202782013-2015. A previous version of this paper was presented at the Second Conference of the Society for Economic Measurement; the Conference on Large-scale Crises: 1929 vs 2008; the 4th ECB/CBRT Conference: Economic Growth and Income Convergence; the 57th Riunione Scientifica Annuale della Società Italiana degli Economisti, the 2017 Quantitative Finance Workshop; the Seventh Meeting of the Society for the Study of Economic Inequality The authors are grateful to conference participants and to two anonymous referees for constructive comments.

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1 Introduction

The disruptive effects of the subprime financial crisis and ensuing sovereign debt crisis have raised new interest on the linkage between financial development and income inequality in the euro area (EA), particularly in the light of the 2.5% average increase in income distribution inequality over the period 2008 through 2013 (Bertola, 2013; D'Errico et al., 2015). The response across euro area countries has however been fairly scattered, consistent with the strong national component in their income distribution (see Gianetti, 2002; Bottazzi and Peri, 2003) and the different degree of social protection and redistributive policies implemented. Countries such as Cyprus, Greece and Spain, where the economic recession was deeper, also experienced a higher than average increase in income inequality; similarly Estonia, France and Slovenia. A higher than average increase in income inequality has also been noted for Austria, Germany, Malta and Slovakia, where redistributive policies were possibly less generous (see Baiardi and Morana, 2016).

The above evidence is consistent with some previous time series, pooled dynamic panel data and panel regression within-country analyses, pointing to an inequality *widening* impact of financial deepening in the short-term. The theoretical underpinning of the "inequality widening hypothesis" can be traced back to Lamoreaux (1986) and Haber (2004), where, due to weak financial institutions or missing financial regulation, financial development operates on the intensive margin, improving financial services only for current users, and leads to higher income inequality. It is also consistent with the view that excess financialization is detrimental to growth, i.e. the "too much finance" phenomenon observed during the subprime financial crisis (Arcand et al., 2015), and the potential effects of banking crisis and financial liberalization policies (de Haan and Sturm, 2016; Furceri and Loungani, 2015). See, for instance, Dabla-Norris et al. (2015) and Denk and Cournède (2015) for recent empirical evidence.

A different view, i.e. the "inequality *narrowing* hypothesis", has also been put forward in the literature, based on the theoretical contributions of Becker and Tomes (1979), Galor and Zeira (1993), Banerjee and Newman (1993). It is posited that capital market imperfections, such as information and transaction costs, impede effective screening/monitoring of investments and risk sharing, and therefore perpetuate cross-dynasty differences in income, wealth allocation, returns to investment, and inequality. Then, by easing credit constraints, financial development reduces dependence on parental wealth and fosters human and physical capital accumulation, economic growth and income equality. Supporting empirical evidence has been provided by various cross-sectional between-country analyses and panel data studies using multi-year averaging. See for instance Beck et al. (2007), Naceur and Zhang (2016) and Delis et al. (2014) for recent results.

Nonlinear features, such as threshold and asymmetric effects, consistent with an inverted U-shape for the finance-inequality relationship, have also been documented in the literature. The "inverted U-shaped hypothesis", can be seen as a combination of the income-narrowing and income-widening hypotheses. It might be grounded on recent contributions to the Kuznets (1955) curve literature that explain its inverse-U shape through the adoption of new technologies and the consequential shift from an unsophisticated to a modern financial system (Greenwood and Jovanovic, 1990; Barro, 2000; Aghion and Howitt, 1997). Hence, when financial markets are underdeveloped, financial development works on the intensive margin, benefits the rich and leads to higher income inequality. However, once a critical threshold is passed, further financial deepening works on the extensive margin, largely benefits the poor and leads to a more egalitarian income distribution. See Nikoloski (2013) and Baiardi and Morana (2016) for recent results. Baiardi and Morana (2016) indeed document a *financial* Kuznets curve (FKC) for the euro area, i.e. a long-term, inverse U-shaped linkage between income inequality and economic development, where financial deepening contributes to a more even distribution of income by lowering the turning point per capita income level. This implies that a country with more developed financial markets reaches the turning point of the Kuznets (1955) curve at a relatively lower income level than a country with a less developed financial system, consistent with a direct linkage between financial deepening and economic growth, and with the view that a threshold level has to be passed before financial development leads to a reduction in inequality.

In the light of the above evidence, the paper further assesses the linkage between financial deepening and inequality for euro area countries since the mid-1980s, with particular reference to the impact of the subprime mortgage and sovereign debt crises. Consistent with its long-run perspective, a financial Kuznets curve for the euro area is estimated by means of cross-sectional methods, in order to exploit between-countries differences in income inequality, as within-country inequality varies only slowly over time (Li et al., 1998). Rather than using conventional OLS or GMM estimation, a novel Frequentist model averaging approach (MAS; Morana, 2015) is implemented. Within this framework, complementary information provided by different financial development and income inequality indicators is jointly exploited, to obtain estimates which are consistent and robust to specification choices. By relying on more degrees of freedom than conventional OLS or GMM, MAS also allows for relatively more efficient estimation.

The original contributions of the study also concern the empirical assessment of the impact of the recent financial crises on income inequality dynamics for the euro area. The latter assessment is particularly relevant, given the scant and conflicting empirical evidence on the effects of financial crises on income inequality available in the literature (see de Haan and Sturm, 2017). By means of a counterfactual analysis, we find higher inequality than would have otherwise occurred in a non-crisis scenario, not only for the countries that were most severely hit by the sovereign debt crisis, but also for core EA countries (Austria, Belgium, Finland, France, Germany and Luxemburg). The finding clearly points to a genuine linkage between financial instability and inequality, since the raise in income inequality appears to be widespread and not confined to the countries that had to implement austerity packages. Consistent with previous evidence of Arcand et al. (2015), we also detect a "too much finance" effect during the recent crises, pointing to inequality falling as financial deepening increases up to a threshold value of 90-100 GDP points, and then rising as financial development progresses beyond the threshold; coherently, the countries that were most affected by the sovereign debt crisis also show the highest figures for both variables.

The rest of the paper is as follows. Section 2 review the relevant literature; Section 3 introduces the FKC and deals with specification and estimation issues; Sections 4 and 5 present the data and empirical results. The empirical properties of the estimated FKCs and convergence issues are then discussed in Section 6, while the impact of the recent financial crises on income distribution is assessed in Section 7. Lastly, conclusions and policy recommendations are reported in Section 8. Additional details are contained in the online Appendix.

2 Literature review

The linkage between financial development, economic growth and income inequality has been widely investigated in the literature, and three main theories have been put forward, i.e. the inequality-widening hypothesis, the inequality-narrowing hypothesis, and the inverted U-shape hypothesis.

The "inequality widening hypothesis" can be traced back to Lamoreaux (1986) and Haber (2004), where, due to weak financial institutions or missing financial regulation, financial development operates on the intensive margin and improves the provision of financial services only for those who are already using them, rather than channeling resources to new users. Under these conditions, primarily the rich and the politically connected benefit from financial development, putting upward pressure on income inequality. The latter scenario is likely to occur during the transition from a traditional sector with simple technology to a modern sector with advanced technology (Clarke et al., 2006). If income inequality is higher in the modern than in the traditional sector, and if the transition to the modern sector requires access to finance, financial development, by fostering the transition to the modern sector, also rises income inequality. Financial liberalization policies might also lead to higher income inequality. For instance, Cragg and Epelbaum (1996) posit that opening the capital account might lead to higher wages inequality by increasing the demand of skilled over non-skilled workers. Harrison (2002) posits that capital account opening might lead to an increase in the profit-wage ratio and to a decrease in the wage share.

On the other hand, the inequality narrowing hypothesis can be related to the work of Becker and Tomes (1979), Galor and Zeira (1993), Banerjee and Newman (1993), where capital market imperfections, such as information and transaction costs, impede effective screening and monitoring of investments and risk sharing. In Becker and Tomes (1979) and Galor and Zeira (1993) imperfect credit markets constrain the access to schooling and capital accumulation for children from less well-off families. Then, by perpetuating cross-dynasty differences in human capital accumulation, credit market imperfections also perpetuate cross-dynasty differences in income and wealth allocation. Due to minimum investment requirements or fixed costs associated with profitable investment, in Banerjee and Newman (1993) only the rich can afford to be entrepreneurs and obtain high returns from their investment; poor people choose instead to work for the entrepreneurs and earn a salary. Hence, the initial distribution of wealth influences the possibility of becoming entrepreneurs and credit constraints perpetuate cross-dynasty returns to investment and income inequality. By easing credit constraints, financial development then reduces dependence on parental wealth and fosters human and physical capital accumulation, economic growth and income equality. More recent contributions, such as Galor and Moav (2004), let the finance-inequality nexus to evolve with the level of economic development. Hence, at early stages of development inequality boosts growth, as, due to credit market imperfections, only the rich -individuals with higher propensity to save- have access to financial resources. This favors the accumulation of physical over human capital, coherent with its higher relative rate of return. However, credit constraints become detrimental to growth at later stages of development, where the return to human capital accumulation exceeds the return to physical capital accumulation, and more dispersed human capital accumulation and a more egalitarian income distribution become essential for economic growth. Similar predictions are obtained by Deidda (2006), where the pro-growth impact of financial development is conditioned to the achievement of a sizable level of economic development. Some theoretical models also predict that financial liberalization policies might improve income distribution. For instance, in the small open economy model of Lim and McNelis (2016) financial liberalization leads to a more egalitarian income distribution once a critical capital intensity threshold is attained, due to redistributive effects of labor productivity gains. Moreover, Bumann and Lensik (2016) show that financial liberalization leads to higher banking sector efficiency and adjustments in interest rates affecting the income of investors and savers, which then lead to lower income inequality, provided financial depth is sizable.

Lastly, the inverted U-shape hypothesis contains elements of both the income inequality narrowing and widening hypotheses, and can be traced back to Greenwood and Jovanovic (1990). It is posited that joining financial intermediation by individuals is costly, but spurs economic growth; in turn, economic growth fosters financial development and income equality by lowering intermediation costs and increasing access to financial services. Hence, the linkage between growth and income inequality depends on the level of financial development. At earlier stages of economic development, where growth and inequality are low, access to financial services is very costly and only few people join intermediaries. As development progresses more people benefit from financial intermediation, leading to faster growth, yet also to higher income inequality. Once a critical financial development threshold is eventually passed, and financial services are further spread to larger shares of population, income inequality then falls, i.e. greater financial development (lower financial intermediation costs) leads to an equilibrium with high growth and low-income inequality, despite transitional dynamics might not be monotonic (Townsend and Ueda, 2006). Hence, a minimum size of the financial sector is required before financial development contributes to a more egalitarian income distribution: below the threshold, financial development operates only on the intensive margin, by channeling more resources to those that already have access to financial markets; as the level of financial/economic development rises and a critical threshold is passed, financial development then operates also on the extensive margin, providing resources to those previously excluded from financial services.

In addition to fixed costs in offering financial services, as in Greenwood and Jovanovich (1990) and the adoption of new technologies shifting the economy from an unsophisticated to a modern financial system (Barro, 2000; Aghion and Howitt, 1997), other theoretical motivations for the existence of a financial development threshold have been related to minimum size requirements for pooling sufficient funds (Acemoglou and Zilibotti, 1997), financial sophistication (Lee, 2006), unequal access to political influence, which create regulatory entry barriers to protect established rents (Rajan and Zinagales. 2003; Perotti and Volpin, 2007), and financial openness, which leads to higher productivity of labor and redistributive effects (Lim and McNelis, 2016).

As detailed below, consistent with the conflicting theoretical predictions, the empirical evidence on the finance-inequality relationship is also not clear-cut. Conflicting evidence might however depend on the horizon of the analysis, since, in general, support for the inequality widening (narrowing) hypothesis is found by studies which exploit within-country (between-country) variability. In this respect, exploiting between-country, rather than within-country variation might provide insights on long- rather than short-term developments in income inequality. In fact, the latter is determined by factors that change slowly within a country over time, but are rather different across countries at any point in time. For the same reason, within-countries studies are then likely to yield insights on short-term income distribution dynamics.

2.1 Empirical evidence on the income inequality-widening hypothesis

Various studies have provided empirical support for the inequality-widening hypothesis, particularly by means of time series and panel data within-country analyses. Results are available for different measures of financial development, i.e. GDP shares of liquid liabilities (M), credit to the private sector (C) or stock market capitalization/total traded value (S); the gross or net Gini index (GI); various cross-sectional and temporal samples.[1] For instance, Jaumotte et al. (2008) consider a sample of 51 advanced, developing and emerging market countries over the period 1981-2003; Jauch and Watzka (2012) a sample of 138 countries for 1960-2008; Dabla-Norris et al. (2015) a panel of 97 countries for 1980-2012; Denk and Cournède (2015) a panel of 31 OECD countries for 1974-2011. In all cases a positive linkage between financial development (C and/or S) and income inequality (GI) is detected by means of OLS within-country estimation.

Additional support is provided by studies using regional data, alternative definitions of income inequality to the Gini Index, or based on time series models and GMM or Bayesian dynamic panel data estimation. For instance, Beltratti and Morana (2007) estimate a small-scale macroeconometric model for the US; they find that a positive stock market shock increases income inequality in the short-term by depressing the wage share. Rodriguez-Pose and Tselios (2009) use a sample of 102 European regions for 1995-2000; they find a positive linkage between the per capita added value of the private financial sector and income inequality (GI). Similar evidence is provided by Roine et al. (2009), Gimet and Lagoarde-Segot (2011), Liu et al. (2016), Seven and Coskun (2016), de Haan and Sturm (2017), Tan and Law (2012). In particular, Roine et al. (2009) use a panel of 16 OECD countries over the period 1866 through 2002; they find that an increase in the stock market capitalization to GDP ratio (S) leads to an increase in the top income percentile (99%). Gimet and Lagoarde-Segot (2011) find a positive linkage between

[1] See also Claessens and Perotti (2007) for earlier, supporting empirical evidence.

the GDP share of private credit (C) and the Estimated Household Income Inequality index (EHII) in a sample of 49 countries for 1994-2002, while de Haan and Sturm (2017) report a similar finding for the Gini Index, in a sample of 121 countries for 1975-2005. Liu et al. (2016) document that an increase in the aggregated credit and stock market capitalization to GDP ratio (C+S) leads to an increase in income inequality (GI) for a panel of 23 Chinese provinces over 1996-2012. Seven and Coskun (2016) use a sample of 45 emerging countries for 1987-2011; they estimate the first principal component among private credit, liquid liabilities, bank deposits, private credit by deposit money banks and other financial institutions, deposit money banks assets to GDP ratios, and find that an increase in the latter index leads to higher inequality (GI). Similar results are reported by Tan and Law (2012) for a panel of 35 developing countries over 1980-2000; in particular, they find a positive linkage between stock market capitalization/total value traded to GDP ratio (S) and income inequality (GI); on the other hand, for the credit to the private sector/liquid liabilities to GDP ratio (C) even a U-shaped relationship is detected, reminiscent of the "too much finance" effect posited by Arcand et al. (2015).

2.1.1 The too much finance effect

By means of cross-sectional and panel regression techniques and a sample of 66 countries for 1960-2010, Arcand et al. (2015) find that the marginal effect of financial depth on output growth becomes negative when credit to the private sector reaches 80-100 per cent of GDP. Confirming evidence is provided by Checchetti and Kharroubi (2012) and Samargandi et al. (2014) for a sample of about 50 countries over the period 1980-2009 and a comprehensive indicator of financial development, yield by the aggregation of the GDP shares of liquid liabilities and private bank credit and the share of commercial banks assets. Various explanations for the phenomenon have been provided in the literature. For instance, short-lived instability episodes of raising macroeconomic volatility and boom-bust financial cycles have been singled out, consistent with previous evidence reported in Borio and Lowe (2004), Kaminsky and Reinhart (1999), Schularick and Taylor (2012). Loayza and Ranciere (2006), using a panel error correction model and a sample of 75 countries for 1960-2000, indeed show that a positive long-run effect of financial development on economic growth coexists with a negative short-term effect, mostly associated with financial crises. The phenomenon has also been related to the consequences of growing misallocation of resources and financial liberalization policies. As argued by Checchetti and Kharroubi (2012), resources allocated to financial investment are unavailable for funding alternative investments in physical and human capital and technological innovation. Due to diminishing returns to financial investment, beyond a critical threshold, financial deepening is then not growth-enhancing any longer, even if the environment is financially sound.

2.1.2 Financial liberalization policies and widening income inequality

Financial liberalization policies, particularly those related to the originate to distribute model, have also been associated with episodes of credit overstretching to low quality borrowers, financial fragility and financial crises. Evidence of a positive impact of financial liberalization policies on income inequality is provided in various studies, using the financial freedom indicators proposed in Abiad et al. (2010; A) and the Fraser Institute's Economic Freedom of the World Index (FI), various samples and dynamic panel data modelling or OLS within-country panel regression estimation. For instance, Das and Mohapatra (2003) use a sample of 11 emerging countries that underwent capital account liberalization between 1986 and 1995; by means of dynamic panel data modelling, they find a positive impact of equity market liberalization on the highest income quintile's share of mean income, a negative impact on the middle-class income share and no impact on the lowest income quintile. A growth-enhancing effect of liberalization is also detected, since, in general, income levels in liberalizing nations rise after policy implementation. de Haan and Sturm (2017) also show that the positive impact of financial liberalization (A, EFI) on income inequality (GI) rises with the level of financial development and the quality of political institutions, for a sample of 121 countries over 1975-2005. Asteriou et al. (2014) use data for the EU-27 countries over 1995-2009 and panel regression estimation; they find that higher capital account openness and a larger foreign direct investment to GDP ratio lead, in general, to higher income inequality (GI). Ang (2010) report similar results for India over 1951-2004, using autoregressive distributed lag modelling and conditioning on several types of interest rate controls and policies directed to credit programs, the cash reserve ratio and the statutory liquidity ratio. Lastly, concerning OLS within-country panel regression results, Jaumotte et al. (2008) use a sample of 51 countries for 1981-2003; they find that a higher stock of inward FDI to GDP ratio is associated with higher inequality. Bergh and Nilsson (2010) find that financial liberalization (EFI) increases inequality (GI) for a sample 79 countries and 1970-2005. Furceri and Loungani (2015) use a panel of 149 countries for 1970-2010; they show that the positive impact of capital account liberalization on income inequality (GI) is larger for countries with weak financial institutions, following financial disruptions, and the lower is the level of financial development (C). Similar results are obtained by Jaumotte and Osuorio Buitron (2015) for 20 advanced economies over 1980-2010, and by Naceur and Zhang (2016) for 143 countries over 1961-2011. In both studies higher inequality is found to be related to domestic and external financial liberalization policies (A).

2.1.3 Financial crises and widening income inequality

The available evidence on the effects of financial crises on income inequality is scant and not clear-cut. For instance, Denk and Cournède (2015), Honohan (2005) and Jaumotte and Osuorio Buitron (2015) do not report any significant impact of banking crises on income inequality. In particular, Honohan (2005) uses a sample of 79 countries for 1980-2000 and compare pre- and post-crisis Gini coefficients by means of cross-sectional regressions. Jaumotte and Osuorio Buitron (2015) use a sample of 20 OECD economies for 1980-2010; they estimate OLS within-country panel regressions including a banking crisis dummy variable, constructed following to the timeline of Laeven and Valencia (2012; LV). Denk and Cournède (2015) follow a similar strategy, using a larger sample of 31 OECD countries for 1974-2011.

In contrast, evidence of a positive linkage between banking crisis and income inequality (GI) is provided by Li and Yu (2014), de Haan and Sturm (2017), Atkinson and Morelli (2011), Baiardi and Morana (2016). Li and Yu (2014) and de Haan and Sturm (2017) find that banking crises lead to higher income inequality for 18 Asian countries over 1996-2005 and 121 countries over 1975-2005, respectively, also using within-country panel regressions, augmented by a crisis dummy variable (LV). Atkinson and Morelli (2011) investigate the impact of banking crises for 25 countries over the period 1911-2010. By comparing pre-crisis and post-crisis inequality data, they point to an increase in inequality in nearly half of the 29 crises investigated. Moreover, by means of a counterfactual exercise comparing post-crisis observation with out-of-sample predicted values, they point to an increase in inequality triggered by financial crises for the majority of episodes, i.e. for seven out of 10 relevant cases. More recently, Baiardi and Morana (2016), show that euro area countries severely hit by the sovereign debt crisis, such as Cyprus, Greece and Spain, but also Estonia, France and Slovenia, experienced a higher than average increase in income inequality. A higher than average increase in income inequality is also found for countries less affected by the recent financial and economic crises, yet where redistributive policies were possibly less marked (Austria, Germany, Malta, Slovakia).

2.2 Empirical evidence on the income inequality-narrowing hypothesis

Supporting empirical evidence for the inequality-narrowing hypothesis is, in general, provided by cross-sectional (between) analyses and panel data studies based on multi-year averaging, to control for business cycle effects. For instance, Li et al. (1998) use a panel of 49 countries for 1974-1994, five-year averaging and OLS/IV pooled panel data estimation; they document a negative relationship between financial development (M) and income inequality (GI); moreover, by splitting the sample into two income groups, the top quintile (the rich) and the bottom quintile (the poor), they find a positive income level effect stronger for poor than rich countries, consistent with diminishing returns to financial investment and economic convergence. Beck et al. (2007) use a sample of 72 countries for 1960-2005 and OLS cross-sectional regression estimation; they find a negative impact of financial development (C) on the Gini Index growth rate, the growth rate of income of the poorest quintile of population, and the fraction of population living in poverty. In particular, the Gini Index and the fraction of population living in poverty tend to fall more rapidly in countries with more developed financial systems; for the latter countries, the income of the poorest quintile also tend to grow faster than the national average. Mookerjee and Kalipioni (2010) use a sample of 70 countries for 2000-2005 and cross-sectional regression estimation; they find a negative impact of the per capita number of bank branches on income inequality. Naceur and Zhang (2016) employ a sample of 143 countries for 1961-2011 and OLS/IV estimation of panel regressions controlling for low, average and high-income country groups; by controlling for various indicators of financial access (per capita number of bank accounts), depth (C, S), efficiency (net margins) and stability (the ratio of regulatory-capital to risk-weighted assets), they also find that financial development leads to a more egalitarian income distribution (GI). Lastly, supporting country-level evidence is provided by Ang (2010) for India over 1951-2004. By means of an autoregressive distributed lag model, he points to a negative linkage between private credit and liquid liabilities to GDP ratios and inequality (GI). Similar results are obtained when financial development is proxied by the number of per capita bank offices.

2.2.1 Financial liberalization policies and narrowing income inequality

Empirical evidence of a negative impact of financial liberalization policies on income inequality have also been found by various studies, still based on OLS within-country panel regression estimation and the indicators provided by Abiad et al. (2010). For instance, Agnello and Sousa (2012) use a sample of 62 countries for 1973-2005; they find that the removal of credit controls, better banking supervision and security market developments have a negative impact on inequality (GI). Similar evidence is reported by Johansson and Wang (2014) for a sample of 90 countries and 1981-2005; Delis et al. (2014) for a sample of 87 countries and 1977-2005; Li and Yu (2014) for a sample of 18 Asian countries and 1996-2005. Conditional effects are also pointed out, since the impact of financial liberalization appears to get stronger with the level of economic development (Delis et al., 2014), the level of human capital (Li and Yu, 2014), and the level of financial development. In this respect, Delis et al. (2014) find that abolishing entry barriers and improving privatization laws lead to lower inequality, particularly in developed countries. Moreover, Bumann and Lensink (2016) find that capital account liberalization lowers income inequality only after a critical threshold in financial development (C) is passed, i.e. only when the private credit to GDP ratio is larger than 25%. Mookerjee and Kalipioni (2010), by means of cross-sectional regression estimation, also find that the removal of checking/saving and loan barriers leads to lower income inequality (GI) for a sample of 70 countries and 2000-2005. Beck et al. (2010) use a fixed effects panel regression for 48 US states over 1996-2005; they find that branching deregulation in the US increased growth and reduced income inequality (GI); the effects of financial liberalizations are found to be strongest among female wage and salary earners and proprietors, and appears to be channelled through both labor market and access to credit. Similar evidence is found when the coefficient of variation of income and the 90th (75th) to 10th (25th) percentile income gap are used to proxy income inequality measures.

2.3 The inverted U-shaped hypothesis

Nonlinear features in the finance-inequality relationship, such as threshold and asymmetric effects supporting the inverted U-shaped hypothesis, have also been documented by various studies, mostly based on cross-sectional (between) analyses and panel data studies using multi-year averaging to control for business cycle effects. In this respect, Clarke et al. (2006) use a sample of 95 countries for 1960-1995 and a panel data regression with five-year averaging; they document an inverse U-shaped relationship between financial development (C) and inequality (GI), consistent with the view that countries with more (less) developed financial systems tend to have lower (higher) income inequality. Kappel (2010) also document threshold features in the finance-inequality relationship for a sample of 78 countries and 1960-2006. By augmenting the panel data regression with a developing country dummy variable interacted with the level of financial development, an overall positive impact of financial deepening on income inequality is detected for developing countries, while a negative effect is found for developed countries. The evidence is robust to the proxy of financial development employed, i.e. the private credit or the stock market capitalization/value traded to GDP ratio and the value of traded shares to market capitalization ratio. Moreover, Kim and Lin (2011) use a panel of 63 countries for 1960-2005 and IV cross-sectional regression estimation; they find an inverse U-shaped relationship also relating the level of financial development (C, S) and changes in income inequality (Gini Index annual growth rate/growth rate of income for the lowest quintile of population). As for Kappel (2010), the evidence is robust to different financial development indicators. Nikoloski (2013), using a sample of 76 countries for 1962-2006 and GMM five-year averaging dynamic panel data modelling, estimates the turning point financial development level at a value of 114% for the private credit to GDP ratio, which is fairly consistent with the threshold value detected by Arcand et al. (2015) for the finance-growth relationship. More recently, Baiardi and Morana (2016) document a long-term, inverse U-shaped linkage between income inequality (GI) and economic development for a sample of 19 euro area countries over the period 1985-2013. In particular, they find that financial deepening (C) contributes to a more even distribution of income by lowering the turning point per capita income level. Hence, a country with more developed financial markets would reach the turning point of the Kuznets (1955) curve at a relatively lower income level than a country with a less developed financial system, consistent with a direct linkage between financial deepening and economic growth and with the view that a threshold level has to be passed before financial development leads to a reduction in inequality.

3 The financial Kuznets curve

Following Baiardi and Morana (2016), consider the model

$$y = a + bx + cx^2 \tag{1}$$

where y is a measure of income inequality, x is real per capita income, and a, b and c are coefficients, with $b > 0$ and $c < 0$ in order for (1) to be consistent with the inverse-U shaped relationship posited by Kuznets (1955), i.e. the Kuznets curve (KC).

The KC turning point ($x^\star$) is obtained by maximizing (1) with respect to x, yielding

$$x^\star = -\frac{b}{2c}. \tag{2}$$

By differentiating (1) with respect to time and substituting (2) we obtain

$$\begin{aligned} \frac{\partial y}{\partial t} &= (b + 2cx)\frac{\partial x}{\partial t} \\ &= \alpha(x - x^\star)g \end{aligned} \tag{3}$$

where $\alpha \equiv 2c < 0$ and $g \equiv \frac{\partial x}{\partial t}$ is the (per capita) income growth rate in each country.

The instantaneous change in economic inequality then depends on the per capita income growth rate g and on the distance of x from its turning point $x^\star$; moreover, assuming $g > 0$, inequality increases when $x < x^\star$ and decreases when $x > x^\star$.

By conditioning the turning point per capita income in (2) to the level of financial development (f), i.e.

$$x^\star = \lambda_0 + \lambda_1 f \tag{4}$$

and substituting (4) in (3), we have

$$\frac{\partial y}{\partial t} = \beta_0[x - (\lambda_0 + \lambda_1 f)]g \tag{5}$$

where λ_0 and λ_1 are parameters, with $\lambda_1 < 0$ implying that a country with more developed financial markets reaches the KC turning point at a relatively lower income level than a country with a less developed financial system. Theoretical motivations can then be found in both the inequality narrowing and the inverted U-shaped hypotheses. Financial development can in fact contribute to economic growth and income inequality by improving the allocation of resources and stimulating the accumulation of human and physical capital and technological innovation (Becker and Tomes, 1979; Galor and Zeira, 1993; Banerjee and Newman, 1993). However, the latter beneficial effects might manifest once a critical financial deepening threshold is passed and coincide with the transition from an unsophisticated to a modern financial system (Greenwood and Jovanovic, 1990; Townsend and Ueda, 2006; Acemoglou and Zilibotti, 1997; Lee, 2006; Rajan and Zinagales. 2003; Perotti and Volpin, 2007; Lim and McNelis, 2016; Barro, 2000; Aghion and Howitt, 1997).

Then, by assuming x, g and f to be constant, equation (5) can be then integrated with respect to time to yield

$$y_t = \mu + \beta_0[x - (\lambda_0 + \lambda_1 f)]gt, \tag{6}$$

where $t = 1, ..., T$ and μ is a constant of integration. By setting variables at their *steady-state* value ($_*$) we then obtain

$$y_* = \mu + \beta_0(x_* g_*) + \beta_1 g_* + \beta_2(f_* g_*) \tag{7}$$

where $\beta_0 \equiv 2\alpha < 0$, as required by the inverse-U shaped relationship between income inequality and the level of economic development posited by the KC; $\beta_2 \equiv -\beta_0\lambda_1 < 0$, consistent with the hypothesis of an inverse relationship between financial development and the turning point of the KC; $\beta_1 \equiv -\beta_0\lambda_0$ can take any value. From the coefficients β_0, β_1 and β_2, the structural parameters of interest λ_0 and λ_1 can then be obtained as $\lambda_0 \equiv -\frac{\beta_1}{\beta_0}$ and $\lambda_1 \equiv -\frac{\beta_2}{\beta_0} < 0$.

3.1 Econometric specification

The linear cross-sectional specification used in our empirical analysis is obtained from (7) by adding k control variables $\mathbf{z}$ and a zero mean i.i.d. error term ε.[2] We then have

$$y_n = \mu + \beta_0(x_n g_n) + \beta_1 g_n + \beta_2(f_n g_n) + \boldsymbol{\delta}'\mathbf{z}_n + \varepsilon_n, \qquad n = 1, ..., N \tag{8}$$

where n refers to the n-th country, $n = 1, ..., N$, and $\boldsymbol{\delta}$ is the $k \times 1$ vector of parameters corresponding to the k control variables $\mathbf{z}_n$.

A logarithmic specification is also employed, replacing the original variables with their log values (apart from g), i.e.

$$\ln y_n = \mu_n^* + \beta_0^* \ln(x_n g_n) + \beta_1^* g_n + \beta_2^* \ln(f_n g_n) + \boldsymbol{\delta}^{*\prime} \ln \mathbf{z}_n + \varepsilon_n^*.^3 \tag{9}$$

[2] See below concerning data assumptions.

[3] From the estimated coefficients β_0^*, β_1^* and β_2^* estimates of the coefficient of interest β_0, β_1 and β_2 can be

3.1.1 Testing the Kuznets and financial Kuznets curve hypotheses

The *KC hypothesis* can then be assessed by testing

$$H_0 : \beta_0 \leq 0 \ (\beta_0^* \leq 0)$$

against the alternative

$$H_1 : \beta_0 > 0 \ (\beta_0^* > 0)$$

using a t-ratio test.

The latter test is similar to the test for U shape proposed by Lind and Mehlum (2010), which is based on the derivative of the KC relative to per capita income. In fact, from (3) one has

$$\frac{\partial y}{\partial x} = \alpha(x - x^\star) \tag{10}$$

and, therefore, the condition $\alpha < 0$ is necessary and sufficient for the inverse-U shape of the KC, since inequality increases when $x < x^\star$ and decreases when $x > x^\star$. Relative to Lind and Mehlum (2010), the proposed approach is then simpler to implement, as it avoids the actual evaluation of the derivative of the KC at selected lower and upper bound per capita income values, and only requires the computation of a standard t-ratio test.

Lastly, the *financial KC hypothesis* can be assessed by testing

$$H_0 : \beta_0 \leq 0 \ (\beta_0^* \leq 0) \ \textit{and} \ \beta_2 \leq 0 \ (\beta_2^* \leq 0)$$

against the alternative

$$H_1 : \beta_0 > 0 \ (\beta_0^* > 0) \ \textit{and/or} \ \beta_2 > 0 \ (\beta_2^* > 0).$$

The latter joint hypothesis can be easily tested using sequential t-ratio testing, by relying on the Bonferroni bound principle. Hence, given the t-ratio statistics t_1 and t_2 and corresponding p-values P_1, P_2 for testing the hypotheses $H_{0,1} : \beta_0 \leq 0$ $(\beta_0^* \leq 0)$ and $H_{0,2} : \beta_2 \leq 0$ $(\beta_2^* \leq 0)$, the Bonferroni multiple test can be implemented by rejecting the joint null hypothesis $H_0 = \{H_{0,1}, H_{0,2}\}$, at the α significance level, if at least one of the p-values is less than $\alpha/2$.

3.2 Estimation of the financial Kuznets curve

Neither income inequality nor financial development are uniquely measured. For instance, income inequality can be measured by the market or net income Gini Index or various top/bottom income distribution quantile ratios; financial development can be measured by the GDP shares of credit to the private sector, liquid liabilities, or stock market capitalization. The selection of a single proxy variable for income inequality and financial development might then be arbitrary and lead to non robust results, also in light of the small cross-sectional dimension available (19 countries/observations).

In order to deal with the above drawback, in the paper we have implemented *model averaging by stacking* estimation (MAS; see Morana, 2015). Relative to alternative approaches, MAS has the advantage of performing model averaging ex-ante in a single step, optimally selecting the model's weight according to the MSE metric; moreover, it is straightforward to implement, only requiring the estimation of a single augmented regression. By jointly exploiting ex-ante all the

easily obtained by resorting to the usual transformations; for instance $\hat{\beta}_0 = \hat{\beta}_0^* \frac{\overline{x_n g_n}}{\overline{y_n}}$, where barred values are sample mean estimates; similarly, $\hat{\beta}_2 = \hat{\beta}_2^* \frac{\overline{f_n g_n}}{\overline{y_n}}$ and $\hat{\beta}_1 = \hat{\beta}_1^* \frac{1}{\overline{y_n}}$. As the above sample mean estimates are all positive, the sign of the slope parameter of interest $\hat{\beta}_0$, $\hat{\beta}_1$ and $\hat{\beta}_2$ is not affected by the transformations, and can be directly obtained from the sign of the estimates $\hat{\beta}_0^*$, $\hat{\beta}_1^*$ and $\hat{\beta}_2^*$.

information available and benefiting from more degrees of freedom, the proposed approach yields robust, consistent and (relatively) more efficient estimation than available ex-post methods.

Hence, consider the regression function

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{11}$$

and suppose that P candidate dependent variables $\mathbf{y}$ are available, i.e. $\mathbf{y}_1$, $\mathbf{y}_2$, ..., $\mathbf{y}_P$, where $\mathbf{y}_p$, $p = 1,..,P$, is a $N \times 1$ column vector of observations, as well as R candidates for *one* of the K regressors in the model, ordered first for simplicity, i.e. $\mathbf{x}_{1r}$, $r = 1,...,R$, yielding up to R candidate design matrices $\mathbf{X}_r$ for $\mathbf{X}$.[4] Moreover, the usual properties of the classical linear regression function (asymptotic case) are assumed to hold.

In principle, up to $P \times R$ alternative disjoint models could be estimated and then averaged ex-post, i.e.,

$$\begin{aligned}
\mathbf{y}_1 &= \mathbf{X}_1\boldsymbol{\beta} + \boldsymbol{\varepsilon}_{1,1} \\
\mathbf{y}_1 &= \mathbf{X}_2\boldsymbol{\beta} + \boldsymbol{\varepsilon}_{1,2} \\
&\vdots \\
\mathbf{y}_1 &= \mathbf{X}_R\boldsymbol{\beta} + \boldsymbol{\varepsilon}_{1,R} \\
&\vdots \\
\mathbf{y}_P &= \mathbf{X}_1\boldsymbol{\beta} + \boldsymbol{\varepsilon}_{P,1} \\
\mathbf{y}_P &= \mathbf{X}_2\boldsymbol{\beta} + \boldsymbol{\varepsilon}_{P,2} \\
&\vdots \\
\mathbf{y}_P &= \mathbf{X}_R\boldsymbol{\beta} + \boldsymbol{\varepsilon}_{P,R.}
\end{aligned} \tag{12}$$

Their union yields the stacked model

$$\mathbf{y}_{\mathbf{P},\mathbf{R}} = \mathbf{X}_{\mathbf{P},\mathbf{R}}\boldsymbol{\beta} + \boldsymbol{\varepsilon}_{\mathbf{P},\mathbf{R}} \tag{13}$$

where $\boldsymbol{\beta}$ is the $K \times 1$ vector of parameters, $\mathbf{y}_{\mathbf{P},\mathbf{R}} = vec\left(\mathbf{i}_R \otimes \left[\begin{array}{cccc} \mathbf{y}_1 & \mathbf{y}_2 & ... & \mathbf{y}_P \end{array}\right]\right)$ is the $(N \times P \times R) \times 1$ vector collecting the P $\mathbf{y}_p$ $(N \times 1)$ vectors, $p = 1,..,P$, which are then stacked on top of one another R times, vec is the vectorization operator, $\otimes$ is the Kronecker product and $\mathbf{i}_R$ a $R \times 1$ unitary vector.[5]

By denoting $\mathbf{X}_* = \left[\begin{array}{cccc} \mathbf{X}_1' & \mathbf{X}_2' & ... & \mathbf{X}_R' \end{array}\right]'$ the $(R \times N) \times K$ matrix obtained by stacking the R candidate design matrices on top of one another, $\mathbf{X}_{\mathbf{P},\mathbf{R}}$ is then the $(P \times R \times N) \times K$ design matrix yield by stacking P times the matrix $\mathbf{X}_*$ on top of itself, i.e. $\mathbf{X}_{\mathbf{P},\mathbf{R}} = \left[\begin{array}{cccc} \mathbf{X}_*' & \mathbf{X}_*' & ... & \mathbf{X}_*' \end{array}\right]'$. Lastly, $\boldsymbol{\varepsilon}_{\mathbf{P},\mathbf{R}} = \left[\begin{array}{ccccccc} \boldsymbol{\varepsilon}_{1,1}' & ... & \boldsymbol{\varepsilon}_{1,R}' & ... & \boldsymbol{\varepsilon}_{P,1}' & ... & \boldsymbol{\varepsilon}_{P,R}' \end{array}\right]'$ is a $(P \times R \times N) \times 1$ vector of disturbances. Hence, the sample size of the stacked model is $S = N \times P \times R$.

The stacked OLS estimator is then computed as

$$\hat{\boldsymbol{\beta}}_{ea} = \left(\mathbf{X}_{\mathbf{P},\mathbf{R}}'\mathbf{X}_{\mathbf{P},\mathbf{R}}\right)^{-1}\mathbf{X}_{\mathbf{P},\mathbf{R}}'\mathbf{y}_{\mathbf{P},\mathbf{R}} \tag{14}$$

$$\tilde{\sigma}_{ea}^2 = \frac{\hat{\boldsymbol{\varepsilon}}_{\mathbf{P},\mathbf{R}}'\hat{\boldsymbol{\varepsilon}}_{\mathbf{P},\mathbf{R}}}{S}. \tag{15}$$

Moreover

$$\sqrt{S}\left(\hat{\boldsymbol{\beta}}_{ea} - \boldsymbol{\beta}\right) \xrightarrow{d} N\left(\mathbf{0}, \sigma^2 \text{plim}\left(S^{-1}\mathbf{X}_{\mathbf{P},\mathbf{G}}'\mathbf{X}_{\mathbf{P},\mathbf{G}}\right)^{-1}\right)$$

[4] In our application, $P = R = 3$, as three measures of income inequality $\mathbf{y}_p$ and three measures of financial deepening $\mathbf{x}_{1r}$ are employed; hence, there are up to $P \times R = 9$ alternative regression models.

[5] Hence, $\mathbf{y}_{\mathbf{P},\mathbf{G}} = \left[\left(\underbrace{\begin{array}{cccc} \mathbf{y}_1' & \mathbf{y}_1' & ... & \mathbf{y}_1' \end{array}}_{1\times(N\times R)}\right)\left(\underbrace{\begin{array}{cccc} \mathbf{y}_2' & \mathbf{y}_2' & ... & \mathbf{y}_2' \end{array}}_{1\times(N\times R)}\right)...\left(\underbrace{\begin{array}{cccc} \mathbf{y}_P' & \mathbf{y}_P' & ... & \mathbf{y}_P' \end{array}}_{1\times(N\times R)}\right)\right]'$.

and therefore

$$\hat{\boldsymbol{\beta}}_{ea} \overset{asy}{\sim} N\left(\boldsymbol{\beta}, \sigma^2 \left(\mathbf{X}'_{\mathbf{P},\mathbf{G}}\mathbf{X}_{\mathbf{P},\mathbf{G}}\right)^{-1}\right).$$

As shown by Morana (2015), the stacked OLS estimator in (14) and (15) can be stated as

$$\hat{\boldsymbol{\beta}}_{ea} = \sum_{r=1}^{G} \check{\mathbf{W}}_r^* \left(\frac{1}{P}\sum_{p=1}^{P}\hat{\boldsymbol{\beta}}_{p,r}\right) \tag{16}$$

$$\tilde{\sigma}^2_{ea} = \frac{1}{G}\sum_{r=1}^{G}\frac{1}{P}\sum_{p=1}^{P}\tilde{\sigma}^2_{p,r} \tag{17}$$

where $\sum_{r=1}^{G}\check{\mathbf{W}}_r^* = \sum_{r=1}^{G}\left[\mathbf{X}'_r\mathbf{X}_r+\mathbf{K}_r\right]^{-1}\left(\mathbf{X}'_r\mathbf{X}_r\right) = \mathbf{I}_K$ and $\mathbf{K}_r = \sum_{i=1,\ i\neq r}^{G}\mathbf{X}'_i\mathbf{X}_i$; $\hat{\boldsymbol{\beta}}_{p,r} = \left(\mathbf{X}'_r\mathbf{X}_r\right)^{-1}\mathbf{X}'_r\mathbf{y}_p$ and $\tilde{\sigma}^2_{p,r} = \frac{\hat{\boldsymbol{\varepsilon}}'_{p,r}\hat{\boldsymbol{\varepsilon}}_{p,r}}{T}$. As shown in (16), ex-ante model averaging estimation of the slope vector $\hat{\boldsymbol{\beta}}_{ea}$ is then computed across all the possible $P \times R$ disjoint estimators $\hat{\boldsymbol{\beta}}_{p,r}$, using MSE-optimal weights; the latter are contained in the $K \times K$ matrices $\check{\mathbf{W}}_r^*$, $r = 1, ..., R$, and are proportional to the relative variation of the candidate regressors. On the other hand, as shown in (17), ex-ante model averaging estimation of the variance $\tilde{\sigma}^2_{ea}$ is equivalent to the arithmetic average of all the $P \times R$ disjoint estimators $\tilde{\sigma}^2_{p,r}$. In contrast to ex-post model averaging, which requires the estimation of all the $P \times R$ alternative models and then their averaging using arbitrary weights, the MAS estimator in (14) and (15) performs the operation in a single step, using MSE-optimal weights. Extension to GMM estimation, also considered in this paper, is straightforward, requiring coherent stacking of the instruments. See Morana (2015) for details, also for the case of violation of the hypothesis of conditional homoskedasticity.

4 The data

The dataset is an unbalanced panel of annual observations for the 19 current euro area member countries, covering the period 1985 through 2013 ($N = 19$ and $T = 28$), i.e. Austria, Belgium, Cyprus, Estonia, Finland, France, Germany, Greece, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, the Netherlands, Portugal, Slovakia, Slovenia and Spain.[6]

Income inequality (y) is measured by means of the *market* (GM) and *net income* (GN) Gini Index, computed using household market and disposable income (post-tax, post-transfer), respectively, as reported in the Standardized World Income Inequality Database (SWIID; Solt, 2016). In the light of its wide use in the empirical literature, the net income Gini Index (GW) reported in the World Income Inequality Database (WIID; UNU-WIDER, 2014) is also employed in the analysis. Gini Index sample averages are employed for estimation.

The level of economic development is measured by real per capita GDP (x) at year 2005 constant prices, obtained by the World Bank Development Indicators Database (2014 Edition). Moreover, three distinct proxies for financial development (f) are employed, i.e. i) the GDP share of credit to the private sector (c), ii) the GDP share of liquid liabilities (m), iii) the GDP share of stock market capitalization (s). Data sources are the International Financial Statistics (IFS) database for c and s; the European Central Bank (ECB) for m. These variables have been widely employed as alternative measures of financial depth in previous studies (see Li et al., 1998; Clarke et al., 2006; Beck et al., 2007; Jaumotte et al., 2008; Rodriguez-Pose and Tselios, 2009; Roine et al., 2009; Kappel, 2010; Kim and Lin, 2011; Gimet and Lagoarde-Segot, 2011 and Jauch and Watzka, 2012).

[6]For Slovakia, Slovenia, Estonia and Lithuania a smaller data set is available, observations starting in 1992, 1995, 1995 and 1991, respectively.

Credit to the private sector is measured by the IFS *Claims on Private Sector* series, which include gross credit from the financial system to individuals, enterprises, non-financial public entities (not included under net domestic credit), and other financial institutions (not included elsewhere). While higher values of its GDP share signal easier access to finance by the private sector, its widening beyond given reference values (80%-100%) is also consistent with growing financial fragility and instability (Borio and Lowe, 2004 and Arcand et al., 2015). Its underlying trend should then provide a reliable measure of financial development, being strongly correlated with alternative measures of access to finance, such as the number of ATMs or the number of bank branches per population or per square mile (Jauch and Watzka, 2012), and the GDP share of total banking assets (Cihak et al., 2013).

The GDP share of liquid liabilities is computed using M3, which, by including total deposits held by the private sector in the banking system, yields a measure of the liability side of the financial system. Higher values of this indicator imply easier access to finance. Moreover, it reflects trust of creditors in the financial system. As a measure of the (inverse) income velocity of circulation of money, it also conveys information on the pace of innovations in the payment system, as for instance those brought about by the introduction of ATMs, the use of card, internet and mobile payments, electronic bill presentment and improvements in infrastructure and security (BIS, 2012). Still, by also reflecting the *monetary overhang* in the economy, higher values of this series might signal incoming macroeconomic/price instability through the *demand-pull* channel of inflation. Hence, also the GDP share of liquid liabilities requires controlling for short-lived fluctuations, in order to yield an accurate measure of financial development.

In addition, the GDP share of stock market capitalization is an indicator of stock market development, measuring the easiness for listed firms of accessing the market to raise capital. Moreover, according to Hall (2001) the capital stock measured by the market value of equities reflects both the tangible and intangible assets firms employ in production, consistent with the notion of aggregate capital stock (physical plus human) postulated in endogenous growth theory. Therefore, the GDP share of stock market capitalization also yields a market-valuation measure of the capital to GDP ratio, potentially conveying information on the linkage between financial development and capital accumulation. As for the two previous measures of financial development, also the latter indicator might not yield univocal signals, especially during boom-bust stock market cycles. This is relevant for our study, given the two major disruptive financial events occurring over the time span investigated, i.e. the burst of the dot-com bubble in the early 2000s and the subprime mortgage cum sovereign debt crisis in the late 2000s and early 2010th. As for credit and M3, we control for boom-bust cycles by conditioning on its underlying trend.

Concerning the estimation of the cross-sectional models in (8) and (9), the variables x and f are then measured by mid-sample (year 2000) estimated trend values,[7] while g is the sample average growth rate of trend real percapita GDP. These transformations of the original series allow to set the analysis within a long-term perspective as in Bradford et al. (2005). Having filtered out short-lived fluctuations, potentially related to various forms of instability, the data employed in the analysis are coherent with a framework where *financial development* is associated with prevailing *economic* and *financial stability.*

Lastly, in order to account for the influence of factors other than economic growth and financial development on income inequality, different control variables are included: *i*) the *age dependency ratio* (DEP);[8] *ii*) the GDP share of *government spending* (PE); *iii*) the *spread* between the interest rate on 10-year government bonds relative to interest rate paid on 10-year German Treasury bonds (SPR); *iv*) the GDP share of exports plus imports (*trade openness;* TRD); *v*) the *population share living in urban areas* (URB). All of the above indicators are

[7] See below for details on trend extraction.

[8] This variable is computed as the ratio of dependent people younger than 15 or older than 64 to the working-age population (15-64 years old).

taken from the World Bank Development Indicators Database (2014), with the only exception of SPR, whose source is the IFS database. Their sample averages are employed for estimation.

Concerning their expected effects, the impact of a higher dependency ratio DEP on inequality is ambiguous. In fact, on the one hand a higher DEP might be expected to be positively correlated with government policies directed to the young and/or the elderly, i.e. to interventions such as family and retirement benefits, which should lessen income inequality (Dreher and Gaston, 2008; Bergh and Nilsson, 2010); on the other hand, a higher DEP might also be associated with a larger share of the population without a regular wage, and therefore positively correlated with income inequality (Wan, 2004). Moreover, as government spending PE is related to the size of the welfare system, the provision of public goods, the degree of intervention in the marketplace and the possible use of redistributive expenditures, PE is expected to be negatively correlated with income inequality. Similarly for the Treasury bills spread SPR, which can be expected to be positively correlated with government spending in the long-term. In addition, international trade theories based on the Heckscher-Ohlin framework imply that trade openness TRD generally exerts downward pressure on the wage of unskilled workers especially in high-income countries. Therefore, TRD is expected to be positively correlated with income inequality (Bergh and Nilsson, 2010). Lastly, an increase in the population share living in urban areas URB is expected lo lead to lower income inequality through the growth enhancing effect of urbanization, yielding higher productivity in the urban sector (Davis and Henderson, 2003; Bergh and Nilsson, 2010).[9]

Data filtering. In order to disentangle short- and long-term components, real per capita GDP and the GDP shares of credit to the private sector, liquid liabilities and stock market capitalization are deterministically filtered. This is also in the light of the short-sample available, which led us to discard stochastic methods. In particular, the trend component for the generic series w_t is estimated by OLS, averaging across the four deterministic specifications nested in the model

$$w_t = \beta_0 + \beta_1 t^{0.5} + \beta_2 t + \beta_3 t^2 + \beta_4 t^3 + \varepsilon_t \qquad t = 1, ..., T$$

i.e. in addition to the above general specification, the models

$$\begin{aligned} w_t &= \beta_0 + \beta_1 t + \beta_2 t^{0.5} + \beta_3 t^2 + \varepsilon_t \\ w_t &= \beta_0 + \beta_1 t + \beta_2 t^{0.5} + \varepsilon_t \\ w_t &= \beta_0 + \beta_1 t + \varepsilon_t \end{aligned}$$

are estimated, where ε_t is a stationary disturbance.

Then, a trend cycle decomposition is computed from each of the above four models, yielding

$$w_t = \hat{w}_{j,t} + \hat{\varepsilon}_{j,t} \qquad j = 1, 2, ..., 4$$

and the final estimates, robust to trend model uncertainty, $w_{trend_t} = \frac{1}{4}\sum_{j=1}^{4} \hat{w}_{j,t}$, $w_{cycle_t} = \frac{1}{4}\sum_{j=1}^{4} \hat{\varepsilon}_{j,t}$.

As the estimated cycle ($\hat{\varepsilon}_j$) is zero-mean by construction, the average trend value in the sample coincides with the sample mean of the actual series.

[9] Consistent with the available literature on income distribution inequality, other control variables were also considered in the analysis: i.e. the *gross tertiary school enrollment ratio*, which captures human capital effects; the *CPI inflation rate*, which yields information on the degree of macroeconomic/price instability; the unemployment rate, which yields information on cyclical goods and labor market conditions. They were never found statistically significant in our regressions.

5 Empirical results

The results of the estimated cross-sectional regressions are reported in Table 1, columns 1-4 and 5-8, for the linear and log-log specifications, respectively. Different models, obtained by varying the set of included control variables (DEP, PE, SPR, TRD, URB), are estimated. Heteroskedasticity consistent standard errors are reported in all cases.

As shown in the Table, parameter estimates are consistent with the underlying theoretical framework, pointing to an inverse-U shaped linkage between inequality and the level of economic development (β_0 parameter) and an inverse linkage between the turning point per capita income level and financial deepening (β_2 parameter). In particular, concerning the KC hypothesis, the estimated β_0 parameter is, as expected, negative and statistically significant for both the linear and log-log specifications; the point estimates yield by our preferred models, selected according to statistical significance and explanatory power, are -0.329 and -0.274, respectively (column 4, for the linear model; column 6, for the log-log model). Implementation of the proposed t-ratio test shows that the KC null hypothesis is not rejected at any significance level, yielding values of -3.576[0.9998] and -6.524[1.000] for the linear and log-log model, respectively. The hypothesis of an inverse relationship between the KC turning point per capita income level and the level of financial development is also not rejected, as the estimated β_2 parameter is negative and statistically significant across specifications, equal to -0.337 and -0.243, for the selected linear and log-log models, respectively. Implementation of the proposed Bonferroni test then yields a minimal p-value of 0.9997 for both models, to be contrasted with the 5% benchmark value of 0.0250, pointing to non-rejection of the FKC null hypothesis at any significance level.[10] Hence, financial development contributes to a more even distribution of income in the EA by lowering the KC turning point per capita income level. Conditional to member countries showing the same structural parameters as for the EA as a whole, we interpret the latter finding also as evidence of ongoing convergence across EA member states toward a common KC turning point per capita income level. In fact, as financial deepening progresses, the per capita income turning point level would get lower and lower; as the zero lower bound applies for this variable, we expect it to stabilize at some low positive value, eventually achieved by all countries.

Lastly, concerning control variables, differences can be noted between the linear and log-log models. In fact, while all the control variables are significant for the linear model, only DEP, PE and SPR have been retained in the log-log specification. The inclusion of URB and TRD might then possibly help to control for some nonlinear features, neglected in the linear model, yet accounted for by the log-log model. In all cases, however, signs are consistent with expectations, as an increase in PE, SPR and URB leads to a more even distribution of income, while an increase in DEP and TRD to a worsening in income equality.

As shown in the online Appendix and in Figure 1, MAS estimates are within the interquartile range of the OLS estimates obtained by means of all the possible submodels embedded in the stacked model, therefore yielding, as expected, a description of the assessed linkage robust to specification choices.[11] OLS results are also robust to measurement error and causality assumptions concerning the linkage between financial development and inequality. In fact, as shown in the online Appendix, when compared with GMM estimates (Table A1), OLS estimates do not show any evidence of misspecification or endogeneity bias. In this respect, the OLS log-log model turns out to be the preferred model, which is then employed for the rest of the analysis. See the Appendix for details.

[10] The t-ratio tests for the hypotheses $H_{0,1}: \beta_0 \leq 0$ ($\beta_0^* \leq 0$) and $H_{0,2}: \beta_2 \leq 0$ ($\beta_2^* \leq 0$) are -3.576[0.9998] (-6.524[1.0000]) and -3.474[0.9997] (-3.471[0.9997]), respectively.

[11] Details on the estimated models are available upon request from the authors.

6 Empirical properties of the financial Kuznets curve

As shown in Table 2 (Panel A), the selected *OLS* log-log model estimate of the turning point for the EA-wide steady-state financial Kuznets curve (SS-FKC) is about €13,000, while the estimated dispersion across estimates is €1,200 ($\hat{x}^*$: €$13,279$ $(1,207)$). Moreover, the net and market Gini Index at the turning point are about 30% and 49%, respectively ($\hat{y}^*_{GN}$: 31%; $\hat{y}^*_{GW}$: 32.2%; $\hat{y}^*_{GM}$: 48.5%).[12]

In Figure 2 we plot the estimated EA-wide SS-FKC, obtained through cubic spline interpolation of the cross plots of the predicted Gini Index against (across-country year-2000) trend real per capita income values. The estimated curve is well behaved, showing the expected inverse-U shape; it is also asymmetric, as income inequality grows faster when per capita income increases toward the turning point than it decreases once the threshold is passed.

6.1 EA member countries steady-state FKC properties

By assuming the same structural parameters as holding for the EA-wide SS-FKC, the turning point for each EA member country SS-FKC can also be computed. Comparison between own-country and area-wide SS-FKCs yields information on the degree of *transitory* divergence across EA member states. The latter is deemed to be transitory in the light of the existence of an EA-wide SS-FKC, and therefore of ongoing convergence toward its turning point, as determined by financial deepening.

In Figure 3, we report the cross-plot of the estimated own-country SS-FKC turning points ($\hat{x}^*_n$) against the corresponding financial development level ($\hat{f}^*_n$), computed as the average of the three financial deepening indicators for each country, measured at mid-sample (year 2000) trend values. Corresponding figures for the EA-wide SS-FKC are also reported for comparison ($\hat{x}^*$: 13,279; $\hat{f}\,^*$: 82.2).

Projecting on the x- and y-axis from the EA-wide SS-FKC values $\hat{x}^*$ and $\hat{f}^*$, the FKC turning point per capita income-financial development space is divided into four regions, i.e. high (low) per capita income and high (low) financial development, high (low) per capita income and low (high) financial development. As shown in Figure 3, the two former regions are empty, due to the inverse relationship between income turning points and financial development.

EA countries can then be clustered into two groups. The first group (DEV) shows high financial development and low SS-FKC turning point per capita income level; it is composed of the original EA members, i.e. Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxemburg, Portugal, Spain.[13] The second group (UDV) shows low financial development and a high SS-FKC turning point per capita income level; it is composed of the most recent member states, particularly Estonia, Latvia, Lithuania, Malta; on the other hand, more similar figures to those found for advanced EA members are shown by Cyprus, Slovakia and Slovenia.

In light of the above evidence, we then average across the two groups of countries, to obtain overall representative figures for the SS-FKC turning point per capita income levels ($\hat{x}^*_{DEV}$ and $\hat{x}^*_{UDV}$). Due to their outlying behavior, trimmed averages, discarding observations for the Netherlands and Lithuania, are also computed.[14]

[12] See the Appendix for computation details. Moreover, as shown in the Tables reported in the Appendix, the estimated turning point ($\hat{x}^*$) is strongly robust to the method employed (OLS, GMM), falling in the range €11,600-€11,800 for the linear model and €13,300-€14,300 for the log-log model. Similarly for the predicted Gini values at the turning point.

[13] The outlying behavior shown by the Netherlands is not surprising, due to the historically low values for GDP shares of liquid liabilities and private credit, relative to the other core euro area members. This is also evident from the estimation of the own-country steady-state FKC, the latter country turning out to be located on its upward sloped portion and showing a negative excess inequality during the crisis (see below). Also somewhat outlying is Finland, due to the relatively low value shown by the financial development indicator.

[14] Lithuania has joined the EA only in December 2015; therefore, it does not actually belong to the EA during the period considered.

As shown in Table 2 (Panel B), (OLS log-log model) reference estimates of the turning point for the two groups of countries are about €10,000 for DEV and €16,000 for UDV, coherent with a financial development gap, between the two groups, of about 23 GDP points. Hence, a -22% contraction in the turning point value might be achievable for the new member countries, through further financial development, down to about €13,000, as estimated for the EA-wide SS-FKC. The contraction in income inequality for UDV countries would also be sizable, particularly when assessed by means of the market income Gini Index GM, i.e. -4%, from 53% to 49% (-2.4% for the net income Gini Index GN).

Predicted Gini index values for the EA member countries can also be computed. In Figure 4 we plot the (OLS log-log model) estimated EA own-country SS-FKCs, obtained through cubic spline interpolation of the cross-plots of the predicted Gini index values against (own-country) trend real per capita income. As is shown in the plots, the two groups of relatively more and less advanced countries can again be singled out. The former group, composed of Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxemburg, Portugal, Spain, as well as Cyprus and Slovenia, coherently shows a downward sloping FKC trend per capita income ($DSFKC$), implicitly exceeding turning point levels since the mid-1980s. On the other hand, an upward sloping FKC can be noted for the latter group, composed of Estonia, Latvia, Lithuania, Malta and Slovakia ($USFKC$). Income inequality can then be expected to fall (increase) as economic growth further progresses for the group of more (less) developed EA countries, *ceteris paribus*.

7 Financial crisis and inequality

The analysis carried out in the previous Section is set within a long-term perspective, where financial deepening exerts a positive effect on economic growth. Within this perspective, financial development does not endanger economic stability through the generation of boom-bust financial cycles. As shown by recent events, financial imbalances can however trigger sizable short-term fluctuations: real EA GDP contracted -5.9% during the subprime mortgage cum sovereign debt crisis (-4.7% in 2009; -1.2% in 2012-2013) and sizable effects on income distribution have also been found (Baiardi and Morana, 2016).

In Table 3 we report figures for the level and rate of growth of the Gini Index during the crisis. In particular, income inequality is computed as the average Gini Index level over the period 2008-2013 (GN, GW, GM), while its rate of change as the relative deviation of the latter average figure from its actual value in 2007 ($GN_{\%}$, $GW_{\%}$, $GM_{\%}$). Similar figures are also computed and reported for trend real per capita income and financial development (x, f; $x_{\%}$, $f_{\%}$).

As shown in Table 3, on average across EA countries, during the period 2008-2013, GM (GN) increased 2.3% (1%); the corresponding figures for x and f are -3.8% and -9.7%, respectively. The response of income and inequality to changes in financial depth is then inelastic: a 1% reduction in the financial development indicator is associated with a -0.4% contraction in real per capita income and a 0.24% (0.1%) increase in the market (net) income Gini Index. However, the evidence at the country level is scattered, also consistent with the strong national component in income distribution (see Gianetti, 2002; Bottazzi and Peri, 2003).

In Figure 5 we report cross-plots for the average market and net income Gini Index, relative to average real per capita income and financial development. As shown in Figure 5, both GN and GM monotonically fall as the level of real per capita income increases (column 1, top to bottom plots), as predicted to occur along the downward sloped portion of the KC. Moreover, a U-shaped linkage relates income inequality and financial development, as GM and GN both decrease as financial deepening raises up to a 90%-100% threshold value, to then increase once the threshold is passed (column 2); a kind of "too much finance" phenomenon can then be noted, where the highest average Gini Index figures, or figures in excess of the threshold, are shown by the countries which were affected the most by the sovereign debt crisis, i.e. Cyprus, Ireland, Portugal, Spain, Greece and Italy.[15]

Lastly, comparisons between net and market income inequality figures are strongly informative about the effectiveness of redistributive policies and automatic stabilizers, particularly for the countries which were most severely hit by the sovereign debt crisis. Among the latter, Spain can be singled out as the EA member country where inequality has increased the most during the crisis, also when the effects of redistributive policies are accounted for (11.3% and 7.3%, for $GM_{\%}$ and $GN_{\%}$, respectively); similarly Greece (6% and 4.3%, for $GM_{\%}$ and $GN_{\%}$, respectively) and Cyprus (2% and 1.9%, for $GM_{\%}$ and $GN_{\%}$). On the other hand, Italy, Portugal and Ireland are the countries where inequality has been affected the least or even decreased, possibly due to redistributive policies (IT: -0.1% and -1.1%; PT: -0.9% and -3.6%; IE: 8.5% and -1.7%, for $GM_{\%}$ and $GN_{\%}$, respectively).

7.1 The Gini index anomaly

In order to gauge further insights on the effects of the crisis, in Table 3 we also report figures for the *Gini Index anomaly* during the crisis period, computed as the average deviation of the actual Gini Index from its predicted value according to the corresponding SS-FKC (GN_a, GW_a, GM_a). Hence, the Gini Index anomaly measures *excess inequality* generated by factors unrelated to economic and financial development trends, allowing for a counterfactual comparison of the effects of the crisis, relative to a non-crisis scenario. As shown in the Table, the anomaly is on average sizable, about 3.5% for GM_a, also when redistributive policies are taken into account (1.5% for GN_a).

In Figure 5 we relate the anomalies to the level of both economic and financial development (columns 3 and 4, respectively). An inverse-U shaped linkage can then be noted for excess inequality and real per capita income, reminiscent of the KC itself, as the anomaly raises until a per capita income threshold of about €25,000 is achieved, to fall thereafter. On the other hand, excess inequality monotonically increases with the level of financial development.

The two groups of relatively more and less advanced countries can then be singled out again; the former shows a positive anomaly falling with the level of economic development, yet increasing with financial deepening (6.3 for GM_a; 3.1 for GN_a); the latter shows a negative anomaly (-3.2% for GM_a; -2.1% for GN_a).

The crisis, through its recessionary impact, has then exercised adverse effects for both groups of countries. In fact, a contraction in real per capita income, occurring along the upward (downward) sloped portion of the FKC, causes a reduction (increase) in income inequality and therefore generates lower (higher) income inequality than predicted under a non-crisis scenario. Consistent with the "too much finance" phenomenon already detected, the positive anomaly is actually largest for the countries most severely hit by the sovereign debt crisis, i.e. Cyprus, Ireland, Portugal and Spain (on average 8.2% for GM_a and 3.6% for GN_a), yet not Greece and Italy (4.8% for GM_a and 0.9% for GN_a), which show financial deepening well in excess of the 90%-100% GDP share threshold. Income distribution has then worsened not only for peripheral EA members, which were most severely hit by the financial crisis, but also for those countries showing much sounder public finances, i.e. Austria, Belgium, Finland, France, Germany and Luxemburg. For the latter members the anomaly is positive and large, not only when assessed using GM_a (5.1% on average), but also once redistributive policies are taken into account (3.1% on average for GN_a).

In the light of the above findings, it is then likely that the raise in income inequality for the countries which were most affected by the crisis is not simply a collateral effect of the "austerity" measures implemented to face the sovereign debt crisis. While austerity measures

[15] It is worth noticing that the estimated threshold values for financial development are very close to those obtained by Arcand et al. (2015) and Borio and Lowe (2004), using different data and econometric techniques.

might have contributed to worsening income distribution, the overall evidence does point to a genuine linkage between financial instability and inequality. The finding is also not in contrast with the beneficial effect of financial development on income distribution, as measured by the financial KC. Boom-bust financial cycles and financial development should be held as separate phenomena. As detailed in Laeven and Valencia (2012), during a banking crisis financial intermediation is severely hampered, due to the swift rise of corporate and financial sectors' defaults and non-performing loans, and the exhaustion of most of the banking system's aggregate capital. Depressed asset prices, sharp increases in real interest rates, credit crunches and sudden reversal in capital flows also occur. The ensuing downturns tend to be deeper and last longer than average contractions (Haugh et al., 2009); sizable effects on income inequality might then be also expected. Hence, a well-functioning financial system and its smooth development appear to be instrumental to both economic growth and a more even income distribution.

8 Conclusions

Within the framework of a financial Kuznets curve (Baiardi and Morana, 2016), where turning point per capita income is conditioned to the level of financial development, the paper provides new evidence on real income convergence for the euro area since the mid-1980s, with a special focus on the subprime and sovereign debt financial crises.

We find strong evidence in favor of an EA-wide steady-state *financial Kuznets curve*, i.e. of a long-term inverse-U shaped linkage between inequality and income development, where financial deepening contributes to a more even distribution of income by lowering the per capita income level at which the turning point of the KC occurs. We hold the latter finding as evidence of ongoing convergence across EA members toward a common turning point per capita income level (about € 13,000).

Comparison of EA-wide and own member country FKCs allows us to single out two groups of countries, composed of the most and the least advanced EA member states, showing turning point per capita income levels of about €10,000 and €16,000, respectively, and a financial development gap of about 23 GDP points. Through further financial deepening, a -20% reduction in turning point per capita income could be then attained by the most recent member countries, as well as a sizable contraction in income inequality (-4%).

The recent financial crises have sizably worsened economic and income inequality conditions for all EA member countries. In fact, a counterfactual analysis, comparing actual and predicted Gini Index figures, points to higher inequality than would otherwise have occurred in a non-crisis scenario also for those countries which were little affected by the sovereign debt crisis. A "too much finance" phenomenon is actually detected during the crisis, since inequality falls as financial deepening increases up to a threshold value of 90-100 GDP points, to then increase as the threshold is passed. Coherently, the countries that were affected the most by the sovereign debt crisis show the highest figures for both variables. It is then likely that the raise in income inequality, for the countries which were most affected by the crisis, is not just a collateral effect of the "austerity" measures implemented to face the sovereign debt crisis. While austerity measures might have contributed to worsening income distribution, the overall evidence does point to a genuine linkage between financial instability and inequality.

From a policy perspective, financial regulation is then called for in order to secure a well-functioning financial system and its smooth development, as financial stability is instrumental not only to foster stable economic growth, but also to achieve a more even distribution of income. In this respect, the stable macroeconomic environment prevailing since the mid-1980s in core EA, as well as in other OECD countries (the so called *Great Moderation*), was temporarily destabilized by the US subprime financial crisis and ensuing Great Recession in the late 2000s (Bagliano and Morana, 2017). This is also the same context where the *Great Divide* phenomenon, i.e. the rise in income inequality ongoing since the mid-1980s in OECD countries, originated. In addition to the traditional explanations related to the effects of globalization, skill-biased technical change, unionization, problems with access to education and the decline in the progressivity of the tax schedule at the upper tail of the income distribution (OECD, 2011), the contribution of financial instability to this phenomenon should not be neglected, at least for the 2008-2013 period.

The latter evidence is not in contrast with the beneficial effect of financial development on income distribution, as measured by the financial KC. Boom-bust financial crises and financial development should be considered as separate phenomena. Actually, during busts financial intermediation is usually severely hampered. Regulatory interventions are then required to promote a more efficient capital allocation, particularly through the removal of entry barriers and favoring larger access to credit and international capital flows. Implicitly, this also requires the correction of all those factors which made an otherwise stable macroeconomic environment unstable, excessive risk taking of financial intermediaries primarily. Well-functioning financial markets, in turn, can be expected to enhance physical and human capital accumulation, technological innovation, economic growth and the achievement of a more egalitarian income distribution. Moreover, as recently noted by Stiglitz (2015), it should also be recalled that "greater equality and improved economic performance are complement". Therefore, reversing the current inequality widening trend is also instrumental to achieve stable and sustained economic growth, since inequality does not only means weak aggregate demand today, but also weak growth over time. Inequality is in fact also inequality of educational, and even nutritional opportunity; inequality also means lower public investments in productivity-enhancing projects, such as public transportation, infrastructure, technology and education. Hence, financial stability should be enumerated with the economic, social and environmental pillars of the Lisbon Strategy, continued in the Europe 2020 Strategy.

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Table 1: Stacked OLS (M.A.S.) estimation results for the linear and log-log model

	Liner model				Log-log model			
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
xg	-0.122**	-0.193***	-0.327***	-0.329***	-0.226***	-0.274***	-0.269***	-0.254***
	(0.054)	(0.065)	(0.105)	(0.092)	(0.039)	(0.042)	(0.044)	(0.042)
g	-0.001	-0.022	-0.114	-0.220***	-0.054	-0.070	-0.057	-0.106
	(0.056)	(0.060)	(0.086)	(0.084)	(0.051)	(0.052)	(0.073)	(0.084)
fg	-0.395***	-0.327***	-0.298***	-0.337***	-0.289***	-0.243***	-0.244***	-0.252***
	(0.080)	(0.098)	(0.102)	(0.097)	(0.066)	(0.070)	(0.071)	(0.069)
DEP	0.648***	0.546***	0.573***	0.576***	0.620***	0.501***	0.499***	0.492***
	(0.054)	(0.050)	(0.056)	(0.056)	(0.054)	(0.045)	(0.047)	(0.050)
PE	-0.526***	-0.540***	-0.571***	-0.533***	-0.444***	-0.460***	-0.457***	-0.439***
	(0.074)	(0.071)	(0.068)	(0.065)	(0.066)	(0.061)	(0.059)	(0.061)
SPREAD	-	-0.214***	-0.233***	-0.337***	-	-0.237***	-0.236***	-0.289***
		(0.063)	(0.062)	(0.074)		(0.058)	(0.058)	(0.073)
TRADE	-	-	0.179*	0.309***	-	-	-0.019	0.022
			(0.106)	(0.100)			(0.070)	(0.077)
URBAN	-	-	-	-0.233***	-	-	-	-0.102
				(0.071)				(0.072)
R-squared	0.560	0.592	0.600	0.626	0.593	0.634	0.634	0.639
Adj. R-squared	0.546	0.577	0.583	0.608	0.580	0.620	0.618	0.621
Hetero	4.634 [0.000]	7.896 [0.000]	7.525 [0.000]	7.365 [0.000]	4.605 [0.000]	8.182 [0.000]	8.000 [0.000]	12.219 [0.000]
Reset2	1.870 [0.173]	12.040 [0.000]	8.350 [0.004]	11.750 [0.000]	1.020 [0.315]	0.010 [0.918]	0.000 [0.962]	0.010 [0.916]
Reset23	11.970 [0.000]	9.710 [0.000]	8.390 [0.000]	7.870 [0.000]	9.120 [0.000]	7.520 [0.000]	8.740 [0.000]	7.010 [0.001]
Normality	0.062 [0.960]	3.080 [0.214]	3.641 [0.162]	5.269 [0.072]	0.977 [0.610]	2.725 [0.256]	2.179 [0.336]	2.537 [0.281]
Obs	171	171	171	171	171	171	171	171

The Table reports the results of stacked OLS estimation for the linear and log-log models (columns 1-4 and 5-8, respectively), with robust standard errors in round brackets. Income inequality is measured by the stacked market (*GM*) and net (*GN* and *GW*) income Gini Index, while financial development *f* by the stacked GDP shares of credit to the private sector (*c*), liquid liabilities (*m*) and stock market capitalization (*s*). The other (stacked) regressors are: *xg*, the product of trend real per capita income at mid sample (year-2000) value (*x*) and its average rate of growth over the 1985-2013 period (*g*); *fg*, the product of the trend financial development index at mid-sample value (*f*) and the trend per capita income average rate of growth (*g*); the average age dependency ratio (*DEP*), government spending (*PE*), population share living in urban area (*URB*), trade openness index (*TRADE*), 10-year Treasury bond rate spread relative to the German T-Bund rate (*SPREAD*). *R-squared* and *Adj. R-squared* are the unadjusted and adjusted coefficient of determination; Hetero is the White test for heteroscedasticity; Reset2 and Reset23 are the Ramsey-Reset functional form tests using squares and squares and cubes of fitted values, respectively; Normality is the Bera-Jarque Normality test; P-values are reported in square brackets. The symbols *, **, *** denotes significance at 10, 5 and 1 per cent level, respectively. The number of observations is denoted by Obs.

Table 2: EA-wide and EA own-country steady-state financial Kuznets curve: turning point real per capita income, inequality and reference level for financial development

	Panel A: EA-wide				
	$\hat{x}^*$	$\hat{y}^*_{GN}$	$\hat{y}^*_{GW}$	$\hat{y}^*_{GM}$	$\hat{f}^*$
EURO AREA	13,279	31.024	32.215	48.498	82.15
	(1,207)	(0.446)	(2.005)	(0.434)	
	Panel B: DEV and UDV EA countries				
	$\hat{x}^*$	$\hat{y}^*_{GN}$	$\hat{y}^*_{GW}$	$\hat{y}^*_{GM}$	$\hat{f}^*$
DEV	12,156	32.450	34.346	53.351	91.573
ex − NL	9,991	33.011	34.921	54.055	95.471
UDV	21,140	35.205	34.378	55.557	65.989
ex − LT	16,236	33.418	32.515	53.338	72.285

Panel A in the Table reports the EA-wide financial Kuznets curve turning point per capita income ($\hat{x}^*$), Gini Index income inequality ($\hat{y}^*_i$; i = *GN*, *GW*, *GM*), and reference level for financial development ($\hat{f}^*$). Estimates are from the selected OLS log-log model. In Panel B the same statistics are reported for the two groups of more (*DEV*) and less (*UDV*) financially developed EA countries, also omitting, for robustness, the outlying countries, i.e., the Netherlands and Lithuania. DEV: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxemburg, Portugal, Spain, the Netherlands; UDV: Cyprus, Estonia, Latvia, Lithuania, Malta, Slovakia and Slovenia.

Table 3: Real per capita income, financial development and Gini Index anomaly and actual values: 2008-2013

Panel A: EA member country figures

	Real per capita income		Financial development		Actual Gini Index						Gini Index Anomaly		
	x	$x_{\%}$	f	$f_{\%}$	GN	$GN_{\%}$	GW	$GW_{\%}$	GM	$GM_{\%}$	GN_a	GW_a	GM_a
Austria	32,761	0.3	103.62	-9.89	27.66	2.85	26.48	1.08	46.34	0.97	2.688	2.38	5.756
Belgium	30,389	-1.83	110.79	-13.96	25.47	-1.19	26.7	1.5	44.57	3.41	2.33	1.826	1.921
Finland	32,192	-5.37	90.05	-2.37	26.18	-0.83	25.78	-1.59	47.57	1.64	5.695	4.67	6.943
France	28,550	-1.58	103.26	-6.7	29.45	5.78	30.18	13.47	49.49	2	2.191	2.977	1.912
Germany	30,475	1.87	99.07	-4.63	28.64	-0.57	29.12	-4.22	50.87	0.35	2.678	4.081	6.706
Greece	16,901	-13.53	106.03	-7.76	33.18	4.34	33.62	-1.98	50.79	6.03	0.79	0.558	5.413
Ireland	38,305	-9.99	143.09	-18.99	29.21	-1.65	29.83	-4.69	54.15	8.52	-0.624	-0.019	7.288
Italy	24,617	-6.75	101.98	-5.1	32.67	-1.05	31.9	2.9	48.84	-0.05	1.166	0.994	4.097
Luxembourg	65,231	-5.81	121.04	-23.87	27.04	-2.04	27.92	1.89	46.15	0.55	2.861	1.979	7.461
Spain	20,973	-5.71	139.16	-3.44	32.83	7.29	33.75	5.8	49.97	11.3	3.779	5.71	9.354
Portugal	15,160	-3.21	127.72	-6.48	34	-3.57	34.72	-5.64	56.08	-0.92	4.211	-0.44	8.031
Netherlands	35,204	-1.4	51.49	-15.29	25.75	-6.01	26.14	-5.28	45.52	-1.9	-0.545	-2.197	-0.274
Slovakia	11,891	5.83	78.91	-33.04	26.17	5.53	25.34	3.41	42.82	2.94	-0.602	-1.571	-2.804
Slovenia	15,599	-4.67	109.1	-11.54	24.77	7.68	23.7	2.14	41.14	3.9	5.333	2.835	9.229
Estonia	9,033	-9.72	81.03	-7.13	32.35	1.59	31.72	-5.02	48.87	5.49	-3.535	-3.521	-3.054
Latvia	3,554	-10.03	78.18	29.11	35.49	-2.41	36.15	2.12	56.7	-2.89	-3.201	-1.658	-5.355
Cyprus	15,467	-4.4	138.13	-11.66	29.98	1.91	29.27	-1.79	48.83	2.03	7.15	5.577	8.228
Malta	13,089	3.66	73.03	-11.28	27.39	0.92	27.62	5.01	44.98	0.9	-1.285	-1.424	-2.14
Lithuania	7,102	0.49	40.55	-19.47	34.65	-0.8	34.33	-1.9	54.83	-0.86	-2.099	-3.616	-2.482

Panel B: Average figures

	Real per capita income		Financial development		Actual Gini Index						Gini Index Anomaly		
	x	$x_{\%}$	f	$f_{\%}$	GN	$GN_{\%}$	GW	$GW_{\%}$	GM	$GM_{\%}$	GN_a	GW_a	GM_a
Average EA	**23,500**	**-3.782**	**99.802**	**-9.657**	**29.625**	**0.935**	**29.698**	**0.379**	**48.869**	**2.285**	**1.525**	**1.008**	**3.486**
DSFKC	**28,201**	**-4.668**	**114.849**	**-9.722**	**29.314**	**1.458**	**29.459**	**0.682**	**48.83**	**3.056**	**3.096**	**2.548**	**6.334**
USFKC	**8,934**	**-1.954**	**70.34**	**-8.362**	**31.21**	**0.966**	**31.032**	**0.724**	**49.64**	**1.116**	**-2.144**	**-2.358**	**-3.167**

Panel A reports average figures for EA member countries *Gini Index anomaly* (GN_a , GW_a , GM_a) and *actual values*, in levels (GN , GW , GM) and rate of growth ($GN_{\%}$, $GW_{\%}$, $GM_{\%}$), over the period 2008-2013. Average figures for trend per capita income and financial development levels (x , f) and rates of growth ($x_{\%}$, $f_{\%}$) are also included. Panel B reports EA-wide average figures and for the two groups with downward (DSFKC) and upward (USFKC) sloped financial Kuznets curves, respectively. DSFKC: Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxemburg, Spain, Portugal, as well as Cyprus and Slovenia; USFKC: Estonia, Latvia, Lithuania, Malta, Slovakia. The outlying figures for the Netherlands are neglected in the computations for USFKC.

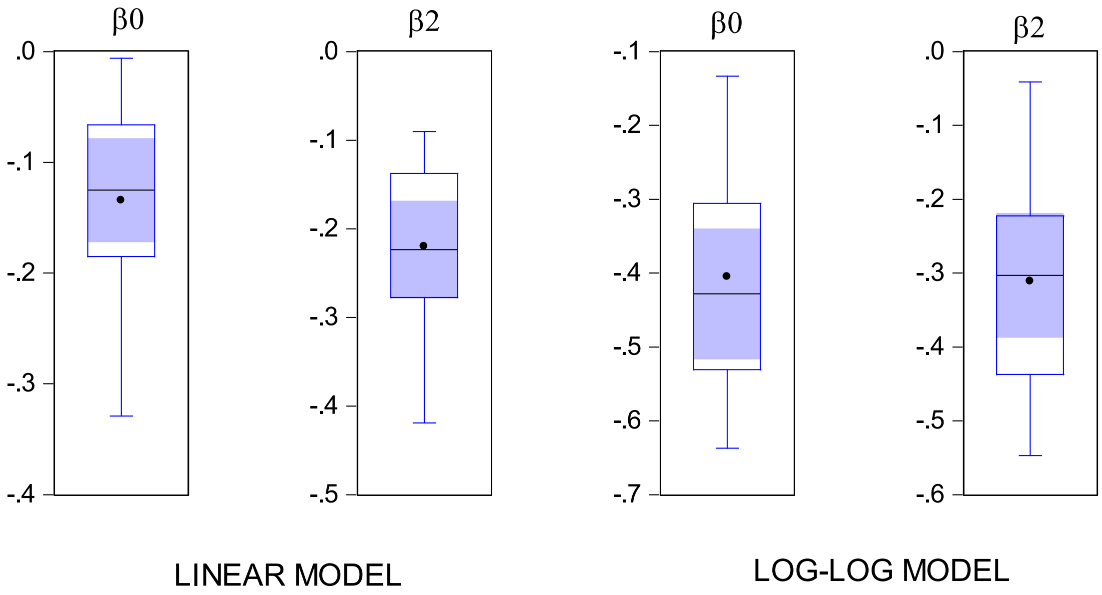

Figure 1: In the Figure box-plots for the estimated β_0 and β_2 parameters from the linear and log-log cross-sectional regressions are reported. The box portion represents the first and third quartiles, while the median is depicted using a line through the center of the box and the mean is drawn using the dot. The difference between the first and third quartiles represents the *interquartile range*, or IQR. The shaded areas refer to the 95% confidence interval about the median, while the outer lines represent the last data point within (or equal to) each of the inner fences, defined as the first quartile minus 1.5*IQR and the third quartile plus 1.5*IQR.

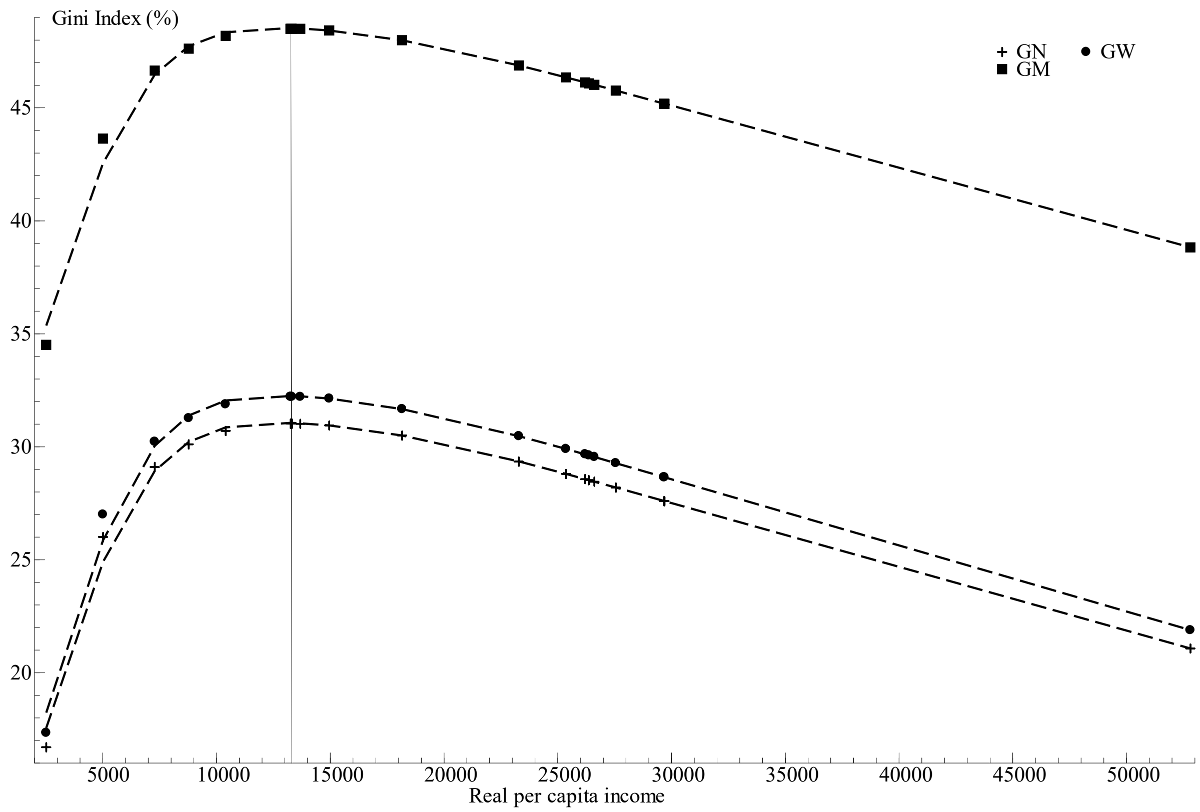

Figure 2: In the plot the estimated EA steady-state financial Kuznets curve (cubic spline interpolation), obtained by means of the preferred OLS log-log model, is plotted with reference to the available three measures of income inequality, i.e., the net (GN) and market (GM) income Gini Index (%).

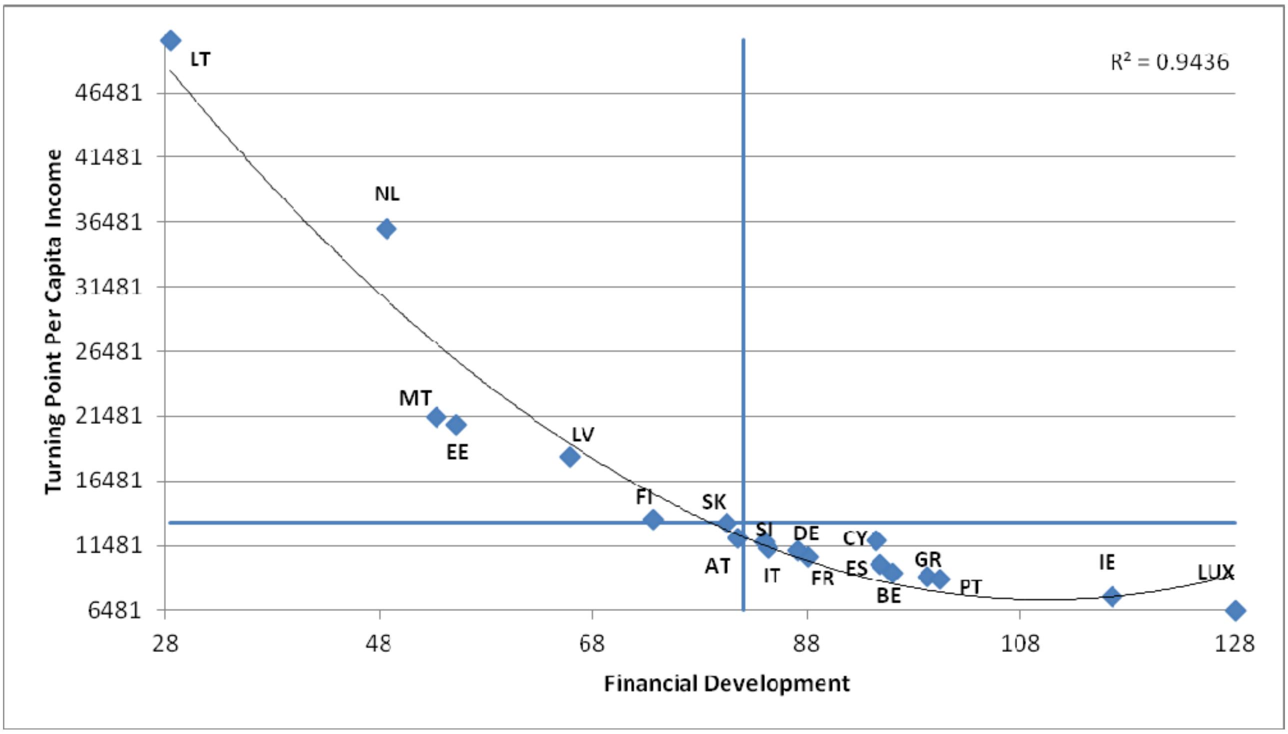

Figure 3: The plot shows the relationship between the EA member countries FKC turning point per capita income (x^*) and the overall level of financial development (*f*). The straight lines are reported in correspondence of the estimated values for the EA steady-state Kuznets curve. In all cases OLS log-log model estimates are reported.

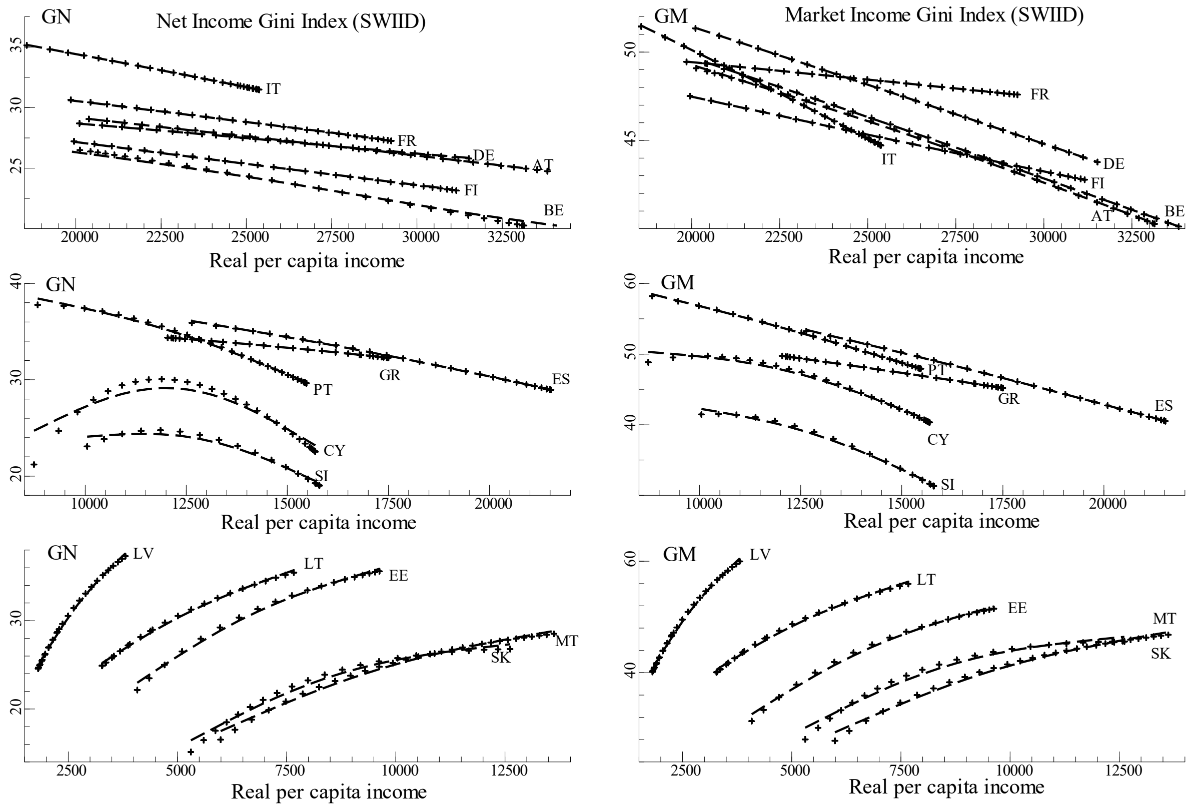

Figure 4: In the plot the estimated financial Kuznets curve for the various EA countries, obtained by means of the preferred OLS log-log model, are plotted with reference to the net (GN) and market (GM) income Gini Index (%). Figures for Ireland, the Netherlands and Luxemburg are not reported for graphical convenience.

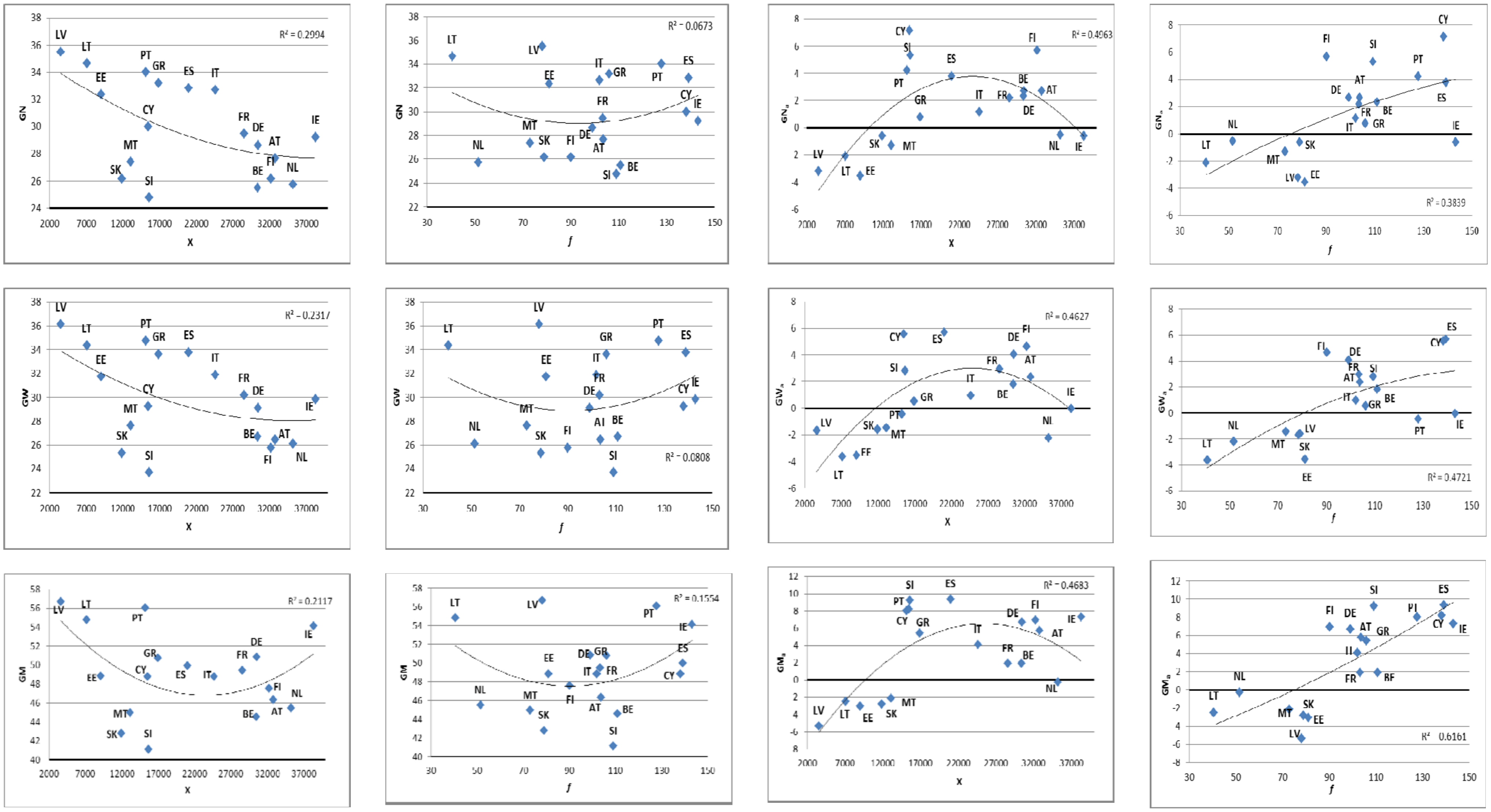

Figure 5: Gini Index levels (*GN*, *GW*, *GM*) and corresponding anomaly values (GN_a, GW_a, GM_a) versus real per capita income (*x*) and financial development (*f*). Figures for Luxemburg are omitted for graphical convenience.

Supplementary Appendix to: "Financial deepening and income distribution inequality in the euro area"

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July 2017

This Appendix presents details on the the robustness analysis (Section A1) and the estimation of the financial Kuznets curve (Section A2).

A1. Robusness analysis

Robustness analysis I: GMM estimation. The aim of GMM analysis is controlling for the potential endogeneity of the level of financial development. In fact, our baseline specification is coherent with the *supply-lead* view, positing financial deepening to be causal for economic growth and, hence, for income distribution. While the supply-lead view appears to be empirically well grounded (see Demirgüç-Kunt and Levine, 2008), other theoretical underpinnings of the linkage between financialization, economic growth and inequality have also been put forward in the literature. The *demand-following* hypothesis, for instance, posits a minor role for finance in economic growth; financial development would be a consequence of economic growth, rather then one of its engines (Patrick, 1966; Lucas, 1988; Chandavarkar, 1992). Moreover, in light of Greenwood and Jovanovic (1990), Bangake and Eggoh (2011), and, more recently, of Laeven et al. (2015), feedback effects between growth, inequality and financial development might also be empirically relevant.

Consistent with the available literature, the regressor of interest, fg, is instrumented using the legal origin dummy variables (LO) suggested by La Porta et al. (1997). The latter are related to the geographical origin of the legal framework, which can be connected with four main traditions, i.e., English, French, German and Scandinavian. Being predetermined and containing information on the degree of enforceability of financial contracts, LO have been proved to be valid instruments (see, among others, Levine et al., 2000; Laeven et al., 2015).[1]

In particular, in the empirical analysis we have jointly employed two sets of instruments: the former composed of the four legal origin dummy variables themselves (LO); the latter composed of the legal origin dummy variables interacted with the rate of growth of per capita income ($LO \times g$). Due to the inclusion of the intercept in the model, only three instruments out of four, for each group, i.e., a total of six instruments, have been used for GMM estimation. Results are reported in columns 1 and 4 of Table A1.

The validity of OLS estimation has been assessed by means of the Hausman test (Exogeneity), comparing OLS and GMM estimates of the parameter β_2. As shown in Table A.1, the (heteroskedasticity-robust) Exogeneity test points to valid OLS estimation for both the linear and log-log models, as the null hypothesis of consistent OLS estimation (weak exogeneity of fg) is never rejected, at the 1% level for the linear model and at a much larger level for the log-log model (22%). Somewhat conflicting results are yield by the Hansen-J statistic, rejecting the null hypothesis of instruments uncorrelated with the

[1] The original dataset of La Porta et al. (1997) has been updated following *The World Factbook List of Legal System*, yielding the following four groups of countries. English tradition (LO_E): Ireland and Malta; French tradiation (LO_F): Belgium, Cyprus, France, Greece, Italy, Luxembourg, the Netherlands, Portugal, Spain; German tradition (LO_G): Austria, Estonia, Germany, Latvia, Slovakia and Slovenia; Scandinavian tradition (LO_S): Finland and Lithuania.

structural equation residuals, and the Kleibergen-Paap rk test (Underidentification), properly rejecting the null hypothesis of uncorrelated instruments with the suspected endogenous variable fg.

In light of the above conflicting evidence, following Lewbel (2012), GMM estimation has been repeated using *generated instruments*, constructed from the residuals of an auxiliary equation regressing fg on all the exogenous variables, including the constant, multiplied by the same regressors (in deviation from the mean). The stronger the degree of scale heteroskedasticity in the structural residuals, the higher will be the correlation of the generated instruments with the included endogenous variables fg. Due to the presence of heteroskedastic errors, the latter generated instruments are then granted to be well behaved in our application.

In Tables A.1 we then report the results of two additional GMM regressions, the former using only generated instruments (columns 2 and 5, respectively), the latter supplementing legal origin dummy variables with generated regressors (columns 3 and 6, respectively). The estimated parameters are strongly robust to the employed instruments, which appear to be valid in all cases according to the Underidentification test, yet only for the log-log model according to the Hansen-J statistic. However, in the latter case estimated parameters are virtually coincident with those obtained using La Porta (1997) instruments (column 5). Moreover, the Exogeneity test points to consistent OLS estimation, at the 5% level, for both the linear and log-log models. Generated instruments GMM also do not improve upon OLS in terms of residual misspecification tests. Finally, OLS and GMM estimates are not statistically different (not reported), inviting the computation of an average OLS and GMM estimate as well, which is denoted as MIX.[2]

In light of the above results, we then regard OLS estimation of the structural parameters of interest valid and robust to endogeneity and measurement error bias; moreover, the log-log model should be preferred to the linear specification.

Robustness analysis II: disjoint estimation. In the second exercise we assess the robustness of OLS estimation of β_0 and β_2 to all the possible specification choices nested in the stacked regression model, i.e. 15 alternative submodels in total. Of the latter, the first nine regressions correspond to the disjoint models obtained by regressing *each* of the three Gini indexes on *each* of the three available financial development indicators. The dependent variable y is therefore defined as GN, GM and GW in turn, while the variable f as c, m and s in turn also. Moreover, three additional regressions are yielded by *partially* stacked models, where the stacked Gini index series $GINI$, composed of GN, GM and GW ($GINI = \begin{bmatrix} GN' & GM' & GW' \end{bmatrix}'$), is regressed on *each* of the available three measures of financial development c, m and s, in turn. Finally, three additional models are yielded by three other partially stacked models, where *each* Gini index, GN, GM and GW, is regressed in turn on the stacked financial development indicator, composed of c, m and s ($f = \begin{bmatrix} c' & m' & s' \end{bmatrix}'$).

Figure 1 (in the main text) reports boxplots for OLS estimated β_0 and β_2 parameters, obtained from the stacked regression in (10) and its 15 nested submodels.[3] As is shown in the plots, the negative linkages between income inequality and economic development (β_0) and between the KC turning point per capita income and financial development (β_2) are strongly robust across specifications.

A2. Empirical properties of the financial Kuznets curve

Details for the computation of the empirical properties of the EA-wide and EA-own member country steady-state financial Kuznets curves are reported below.

The EA-wide steady-state FKC turning point per capita income. On the basis of the estimated structural parameters λ_0 and λ_1, the turning point of the EA-wide steady-state FKC is then computed using (4) as

$$\hat{x}^{\star} = \hat{\lambda}_0 + \hat{\lambda}_1 \hat{f}^{*}$$

where $\hat{f}^{*}$ is the across-country average of the financial development variable, as yielded by the average of the GDP shares of credit to the private sector (c), liquid liabilities (m) and stock market capitalization (s), each measured by its trend value at mid-sample (year 2000). Three estimates of the turning point income level are then available, for each specification, according to the estimator employed in (6) and (7), i.e.,

[2] The p-value of the test for the difference of the β_0, β_1, and β_2 parameters obtained from OLS and GMM estimation are, in fact, 0.864, 0.898 and 0.841, respectively, for the linear model; 0.473, 0.573 and 0.315, respectively, for the log-log model.

[3] A full set of results is available upon request from the authors.

OLS ($\hat{\lambda}_{i_{OLS}}$; $i = 0, 1$), GMM ($\hat{\lambda}_{i_{GMM}}$; $i = 0, 1$), as well as their average (MIX) ($\hat{\lambda}_{i_{MIX}} = \frac{\hat{\lambda}_{i_{OLS}} + \hat{\lambda}_{i_{GMM}}}{2}$; $i = 0, 1$).

Since standardized variables were employed in the estimation of (7) and (8), $\hat{x}^\star$ for the linear model is

$$\begin{aligned}\hat{x}^\star &= \bar{x}_x + \left(\hat{\lambda}_0 + \hat{\lambda}_1 f^*\right)\hat{\sigma}_x \\ &= \bar{x}_x + \hat{\lambda}_0 \hat{\sigma}_x\end{aligned}$$

while for the log-log model one has

$$\begin{aligned}\hat{x}^\star &= \exp\left(\bar{x}_{\ln x} + \left(\hat{\lambda}_0 + \hat{\lambda}_1 \ln \hat{f}^*\right)\hat{\sigma}_{\ln x}\right) \\ &= \exp\left(\bar{x}_{\ln x} + \hat{\lambda}_0 \hat{\sigma}_{\ln x}\right)\end{aligned}$$

where $\bar{x}_x$ ($\bar{x}_{\ln x}$) is the average of mid-sample (year 2000) trend (log trend) real per capita income values across-country, and $\hat{\sigma}_x$ ($\hat{\sigma}_{\ln x}$) its sample standard deviation. Results are reported in Table A.2.

Implied inequality values by the EA-wide steady-state FKC. Predicted EA-wide Gini Index values can be obtained from (1) as

$$\tilde{y}_{GINI,n} = \hat{b}_{LM} x_n + \hat{c}_{LM} x_n^2$$

$$\tilde{y}_{GINI,n} = \exp\left(\hat{b}_{LL} \ln x_n + \hat{c}_{LL} \ln x_n^2\right)$$

for the linear (LM) and log-log (LL) models, respectively, where $GINI = GN, GM, GW$; x_n is trend real per capita income at mid-sample value (year 2000) for the generic nth country, $n = 1, 2, ...19$. Moreover, according to the theoretical framework, $\hat{c}_{LM} = \hat{\beta}_0^{LM}/2$, $\hat{b}_{LM} = -\hat{\beta}_0^{LM} \times \hat{x}^*$, $\hat{c}_{LL} = \hat{\beta}_0^{LL}/2$, $\hat{b}_{LL} = -\hat{\beta}_{0_j}^{LL} \times \hat{x}^*$, where $\hat{\beta}_0^{LM}$ and $\hat{\beta}_0^{LL}$ is the destandardized $\hat{\beta}_0$ obtained from the linear and log-log models, respectively, and the selected OLS log-log model estimate of the FKC turning point real per capita income level ($\hat{x}^*$) is employed in all cases. According to the estimator employed, i.e., OLS, GMM, MIX, three different set of values are then available for each inequality indicator.

As the unknown scaling factor a in (1) is neglected in the formulas for $\hat{x}^*$ above, the scaled estimate of the Gini index is obtained by applying the standardization

$$\hat{y}_{GINI,n} = \hat{\mu}_{GINI} + \hat{\sigma}_{GINI}\left(\frac{\tilde{y}_{GINI,n} - \bar{y}_{GINI}}{\bar{\sigma}_{\tilde{y}_{GINI}}}\right) \tag{1}$$

where $\hat{\mu}_{GINI}$ is the average across countries and time of the Gini index variable, $GINI = GN, GM, GW$ and $\hat{\sigma}_{GINI}$ its sample standard deviation; $\bar{y}_{GINI}$ is the sample mean of the predicted figures $\tilde{y}_{GINI,n}$ and $\bar{\sigma}_{\tilde{y}_{GINI}}$ the corresponding sample standard deviation. Results are reported in Table A.2.

The EA member countries steady-state FKC. By assuming the same structural parameters as holding for the EA-wide steady-state financial Kuznets curve, the turning point for each EA member country steady-state FKC can be computed from (4) as well, yielding, for the generic nth country, $n = 1, ..., 19$

$$\hat{x}_n^* = \bar{x}_x + \left(\hat{\lambda}_0 + \hat{\lambda}_1 \hat{f}_n^*\right)\hat{\sigma}_x \tag{2}$$

$$\hat{x}_n^* = \exp\left(\bar{x}_{\ln x} + \left(\hat{\lambda}_0 + \hat{\lambda}_1 \ln \hat{f}_n^*\right)\hat{\sigma}_{\ln x}\right) \tag{3}$$

for the linear and log-log model, respectively. In the above formula $\hat{f}_n^*$ is the average of the three (standardized) financial deepening variables available (c_n, m_n, s_n) for each country n, measured at mid-sample (year 2000) trend value and $\ln \hat{f}_n^*$ the average of their (standardized) logs; $\bar{x}_x$ ($\bar{x}_{\ln x}$) is the across-country average of trend (log trend) real per capita income at mid-sample (year 2000) value and $\hat{\sigma}_x$ ($\hat{\sigma}_{\ln x}$) its sample standard deviation. Hence, six distinct turning point per capita income estimates are available for each country, according to functional form specification (linear and log-log) and estimator (LS, GMM, MIX). Results are reported for the two groups of DEV and UDV countries, as discussed in the main text, in Table A.2.

Implied inequality values by the EA own-country steady-state FKCs. As for the EA-wide case, predicted EA member country Gini index values can be computed from (1) as

$$\tilde{y}_{GINI,n,t} = \hat{b}_{LM} x_{n,t} + \hat{c}_{LM} x_{n,t}^2 \qquad t = 1, ..., T$$

for the linear model, and

$$\tilde{y}_{GINI,n,t} = \exp\left(\hat{b}_{LL} \ln x_{n,t} + \hat{c}_{LL} \ln x_{n,t}^2\right)$$

for the log-log model, where $x_{n,t}$ is real trend per capita income for country n at time period t, and all the other terms are defined as above.

Moreover, scaled Gini Index estimates can be coputed as

$$\hat{y}^*_{GINI,n,t} = \hat{\mu}_{GINI_n} + \hat{\sigma}_{GINI_n} \left(\frac{\tilde{y}_{GINI,n,t} - \bar{y}_{GINI,n}}{\bar{\sigma}_{\tilde{y}_{GINI,n}}} \right) \qquad t = 1, ..., T$$

where $\hat{\mu}_{GINI_n}$ is the sample mean of the Gini index variable for country n, computed over the available time period, $GINI = GN, GM, GW$, and $\hat{\sigma}_{GINI,n}$ its sample standard deviation; $\bar{y}_{GINI,n}$ is the sample mean of the predicted figures $\tilde{y}_{GINI,n,t}$ and $\bar{\sigma}_{\tilde{y}_{GINI,n,}}$ its sample standard deviation. Six different sets of predicted values for each Gini index are then obtained for each country, according to functional form specification (linear and log-log) and estimator (LS, GMM, MIX). Results are reported for the two groups of DEV and UDV countries, as discussed in the main text, in Table A.2.

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Table A1: Stacked GMM (M.A.S.) estimation results for the linear and log-log models

	Linear model			Log-log model		
	(1)	(2)	(3)	(4)	(5)	(6)
xg	-0.297*	-0.315**	-0.332***	-0.211***	-0.211***	-0.254***
	(0.163)	(0.142)	(0.115)	(0.077)	(0.059)	(0.049)
g	-0.203**	-0.212**	-0.221**	-0.032	-0.032	-0.058
	(0.103)	(0.099)	(0.088)	(0.043)	(0.063)	(0.050)
fg	-0.386*	-0.358*	-0.332**	-0.379***	-0.379***	-0.286***
	(0.224)	(0.185)	(0.146)	(0.116)	(0.141)	(0.077)
DEP	0.584***	0.579***	0.575***	0.527***	0.526***	0.509***
	(0.066)	(0.058)	(0.059)	(0.039)	(0.059)	(0.046)
PE	-0.544***	-0.538***	-0.531***	-0.508***	-0.508***	-0.475***
	(0.078)	(0.068)	(0.066)	(0.059)	(0.089)	(0.064)
SPREAD	-0.332***	-0.335***	-0.338***	-0.222***	-0.222***	-0.232***
	(0.081)	(0.076)	(0.075)	(0.061)	(0.062)	(0.060)
TRADE	0.302***	0.306***	0.309***	-	-	-
	(0.100)	(0.102)	(0.098)			
URBAN	-0.238***	0.235***	-0.232***	-	-	-
	(0.073)	(0.073)	(0.072)			
R-squared	0.626	0.626	0.626	0.626	0.626	0.633
Hetero	6.924 [0.000]	7.159[0.000]	7.419[0.000]	7.103 [0.000]	7.100 [0.000]	7.844 [0.000]
Reset2	10.820 [0.001]	n.a.	n.a.	0.830 [0.363]	n.a.	n.a.
Reset23	8.010 [0.000]	n.a.	n.a.	0.680 [0.509]	n.a.	n.a.
Normality	4.541 [0.103]	4.930[0.085]	5.358[0.069]	5.296 [0.071]	5.307 [0.070]	3.384 [0.184]
Underidentification	18.76 [0.004]	15.882 [0.026]	33.730 [0.001]	34.903 [0.000]	19.388 [0.001]	55.225 [0.000]
Hansen J	22.435 [0.000]	30.459 [0.000]	52.992 [0.000]	15.384 [0.009]	8.024 [0.091]	23.471 [0.009]
Exogeneity	5.946 [0.015]	2.234 [0.135]	3.785 [0.052]	1.857 [0.173]	0.795 [0.372]	0.142 [0.706]
Obs	171	171	171	171	171	171

The Table reports the results of stacked GMM estimation for the linear and log-log models (columns 1-3 and 4-6 respectively), with robust standard errors in round brackets. Income inequality is measured by the stacked market (*GM*) and net (*GN* and *GW*) income Gini Index, while financial development *f* by the stacked GDP shares of credit to the private sector (*c*), liquid liabilities (*m*) and stock market capitalization (*s*). The other (stacked) regressors are: *xg*, the product of trend real per capita income at mid sample (year-2000) value (*x*) and its average rate of growth over the 1985-2013 period (*g*); *fg*, the product of the trend financial development index at mid-sample value (*f*) and the trend per capita income average rate of growth (*g*); the average age dependency ratio (*DEP*), government spending (*PE*), population share living in urban area (*URB*), trade openness index (*TRADE*), and 10-year Treasury bond rate spread relative to the German T-Bund rate (*SPREAD*). Results for GMM estimation performed using La Porta et al. (1997) instruments are reported in columns 1 and 4, while columns 2 and 5 report estimation results when Lewbel (2012) instruments are employed; GMM results in columns 3 and 6 refer to the case in which La Porta et al. (1997) and Lewbel (2012) instruments are employed jointly. *R-squared* is the unadjusted coefficient of determination; Hetero is the White test for heteroscedasticity; Reset2 and Reset23 are the Ramsey-Reset functional form tests using squares and squares and cubes of fitted values, respectively; Normality is the Bera-Jarque Normality test; Underidentification is the Kleibergen-Paap rk underidentification test; Hansen J is the Sargan-Hansen instruments validity test; Exogeneity is the Hausman test for the weak exogeneity of the interacted financial development variable *fg*. P-values are reported in square brackets. The symbols *, **, *** denotes significance at 10, 5 and 1 per cent level, respectively. The number of observations is denoted by Obs.

Table A.2: EA-wide steady-state financial Kuznets curve: turning point real per capita income, inequality and reference level for financial development

	$\hat{x}^*$	$\hat{y}^*_{GN}$	$\hat{y}^*_{GW}$	$\hat{y}^*_{GM}$	$\hat{f}^*$
Linear model					
OLS	11,771	30.121	31.277	47.631	82.150
GMM	11,595	30.083	31.287	47.564	82.150
MIX	11,683	30.106	31.262	47.616	82.150
Log-log model					
OLS	13,279	31.024	32.215	48.498	82.150
	(1,207)	(0.446)	(2.005)	(0.434)	
GMM	14,327	30.789	26.834	48.272	82.150
MIX	13,973	30.904	32.090	48.382	82.150

The Table reports EA-wide financial Kuznets curve turning point per capita income ($\hat{x}^*$), Gini Index income inequality ($\hat{y}^*_i$; i = *GN*, *GW*, *GM*) and reference level for financial development ($\hat{f}^*$). Reported estimates are obtained by means of the linear and log-log models and the *OLS*, *GMM* and *MIX* estimators. The sample standard deviation of the various turning point estimates is reported in round brackets, below the selected OLS log-log model estimates.