Macroeconomic Consequences of Income Inequality: Evidence from Panel Data Econometrics

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Zusammenfassung

Seit den 1980er Jahren ist es in den meisten hochentwickelten Volkswirtschaften, aber auch in vielen Entwicklungs- und Schwellenländern, zu einem ausgeprägten Anstieg der Einkommensungleichheit gekommen. Die vorliegende Dissertation untersucht die makroökonomischen Auswirkungen dieser Entwicklung anhand aktueller empirischer Methoden. Die Arbeit baut dabei auf drei eigenständigen Studien auf, die verschiedene Effekte einer sich verändernden Einkommensverteilung beleuchten. Im Mittelpunkt steht insbesondere die Frage, ob eine zunehmende Ungleichheit nachhaltiges Wachstum verhindert.

Die Analysen in dieser Dissertation basieren auf makroökonomischen Datensätzen, die aus einer Vielzahl von Ländern bestehen und welche über mehrere Jahrzehnte hinweg beobachtet werden. Die Variationen innerhalb dieser Daten werden anhand verschiedener Methoden der Paneldatenökonometrie auf den Einfluss der Einkommensverteilung untersucht. Neben einer erhöhten Präzision der Schätzungen im Vergleich zur Analyse von reinen Zeitreihen- oder Querschnittsdaten, bieten Paneldatenregressionen vor allem den Vorteil, dass Verzerrungen aufgrund von nicht beobachtbaren Länderunterschieden meist vermieden werden können.

Nach einem einleitenden Abschnitt dreht sich das zweite Kapitel um den Effekt einer sich verändernden Lohnquote. Die Lohnquote, welche den Arbeitnehmeranteil am Volkseinkommen und damit die Verteilung zwischen Arbeit und Kapital bemisst, ist seit den 1980er Jahren in der Mehrzahl der hochentwickelten Volkswirtschaften zurückgegangen. Gemäß der post-keynesianischen Theorie, die außer durch John Maynard Keynes (1936) vor allem von Michal Kalecki (1971) geprägt wurde, wären hierdurch Verschiebungen in

der gesamtwirtschaftlichen Nachfrage zu erwarten. Ausgehend von einer höheren Konsumneigung aus dem Lohneinkommen im Vergleich zum Kapitaleinkommen, müsste bei einer sinkenden Lohnquote die Konsumnachfrage geschwächt werden. Aus neo-klassischer Sicht könnten sich andererseits aufgrund gesunkener Lohnkosten auch eine steigende Profitabilität der Unternehmen und damit steigende Investitionen neben höheren Nettoexporten ergeben.

Das Kapitel analysiert die relative Bedeutung dieser Effekte anhand von Daten aus 23 hochentwickelten Volkswirtschaften. Anders als in der bestehenden Literatur, werden dabei vor allem langfristige Effekte geschätzt, um mögliche konjunkturelle Verzerrungen zu vermeiden. Dabei wird ein starker positiver Zusammenhang zwischen der Entwicklung der Lohnquote und der gesamtwirtschaftlichen Konsumquote festgestellt. Es ergibt sich für den Beobachtungszeitraum von 1961-2015 aber auch ein langfristig negativer Zusammenhang zwischen der Lohnquote und der Investitionsquote. Während letzterer in den Jahren nach 1991 insignifikant wird, lässt sich nach Berücksichtigung der Kreditentwicklung jedoch feststellen, dass in den letzten Jahrzehnten sinkende Lohnquoten häufig mit steigenden Nettoexporten einhergingen. In Anbetracht unterschiedlich ausgeprägter Einkommensverschiebungen und aufgrund von Hinweisen auf eine große länderspezifische Heterogenität der geschätzten Effekte, lassen sich die Ergebnisse des Kapitels als Erklärungsbeitrag für die seit Ende der 1990er Jahre enorm gewachsenen Leistungsbilanzungleichgewichte interpretieren. Die länderspezifische Heterogenität der Ergebnisse wirft jedoch auch die Frage auf, ob es sich bei der Lohnquote nicht um ein zu grobes Instrument der Verteilungsmessung handelt, da mit dieser nicht die jeweilige Verteilung innerhalb der Arbeits- oder Kapitaleinkommen berücksichtigt wird.

Das dritte Kapitel widmet sich daher der Verteilung der verfügbaren Netto-Haushaltseinkommen, die durch Gini-Koeffizienten aus der Standardized World Income Inequality Database (SWIID) gemessen wird. Das Kapitel konzentriert sich vor allem auf den Einfluss der Einkommensverteilung auf das Sparen des Haushaltssektors, welches im unmittelbaren Zusammenhang mit der keynesianischen Theorie steht. Angesichts einer wachsenden Einkommensungleichheit würde die keynesianische Theorie, aufgrund einer zunehmenden Konzentration von Einkommen in Haushalten mit hohen Sparneigungen, eine ansteigende gesamtwirtschaftliche Sparquote prognostizieren. Da in mikroökonometrischen Studien als Reaktion auf überproportional steigende Spitzeneinkommen aber auch ein Rückgang der Sparquote bei Haushalten der Mittelschicht beobachtet wurde, ist der Gesamteffekt jedoch insgesamt unklar und somit ein interessantes Feld für eine Analyse anhand von makroökonomischen Paneldaten.

Einhergehend mit einer insgesamt widersprüchlichen empirischen Literatur, findet sich kaum Evidenz für einen linearen Zusammenhang zwischen der Einkommensverteilung und der Sparquote des Haushaltssektors. Es ergibt sich jedoch ein konkaver Zusammenhang, der zahlreiche Robustheitstests übersteht. Der marginale Effekt der Einkommensverteilung scheint also vom Niveau der Ungleichheit abzuhängen. Ausgehend von einer relativ gleichmäßigen Einkommensverteilung ist der Effekt einer zunehmenden Einkommenskonzentration auf die Sparquote zunächst positiv, während ab einem Gini der Nettoeinkommen in Höhe von etwa 30 die steigende Ungleichheit zunehmend negativ auf die Sparquote einwirkt. Der Effekt der Ungleichheit scheint außerdem von der Kreditverfügbarkeit abzuhängen. Während zunehmende Ungleichheit bei einem geringen Kreditvolumen eher positiv auf die Sparquote wirkt, lässt sich bei einem hohen Kreditvolumen ein negativer Effekt feststellen.

Das vierte und letzte Kapitel analysiert schließlich direkt den Einfluss der Einkommensverteilung und der staatlichen Umverteilung auf das Wirtschaftswachstum. Die sehr ausführliche Literatur zu diesem Thema wird insbesondere durch die Überprüfung von Wirkungskanälen und die Nutzung eines neuartigen Maßes für die staatliche Umverteilung erweitert. Letztere wird durch die Differenz zwischen Gini-Koeffizienten der am Markt erwirtschafteten Brutto-Einkommen und Ginis der verfügbaren Netto-Einkommen gemessen. Dank jüngster Fortschritte bei der Verfügbarkeit von konsistent berechneten Verteilungsdaten in der SWIID, kann die effektive staatliche Umverteilung über Steuern und Transfers so für eine Vielzahl von Ländern relativ gut erfasst werden. Grundsätzlich gehen viele Ökonomen davon aus, dass staatliche Umverteilung das Wirtschaftswachstum durch negative Anreizwirkungen beeinträchtigen sollte, womit für die Wirtschaftspolitik ein Zielkonflikt zwischen Gleichheit und Effizienz entsteht.

Für den gesamten Datensatz, der sich aus bis zu 154 Länder zusammensetzt, wird im vierten Kapitel ein signifikant negativer Einfluss der Ungleichheit auf das Wirtschaftswachstum festgestellt. Unter Berücksichtigung dieses Effektes im Regressionsmodell, zeigt sich jedoch auch ein negativer Einfluss der staatlichen Umverteilung in ähnlicher Größenordnung. Zusammen heben sich der negative direkte Einfluss der Umverteilung und der positive indirekte Effekt über die resultierende gleichmäßigere Verteilung der Nettoeinkommen gegenseitig auf, so dass die Hypothese eines allgemeinen Zielkonflikts zwischen Gleichheit und Effizienz verworfen werden kann. Die beste Wachstumsperformance scheinen allerdings jene Länder zu verzeichnen, die eine gleichmäßige Einkommensverteilung bei geringer staatlicher Umverteilung erreichen.

Die negative Wachstumswirkung der Ungleichheit wird empirisch auf ein geringeres Bildungsniveau der Bevölkerung und eine höhere Fertilitätsrate zurückgeführt. Es bieten sich damit Hinweise auf aus der Theorie bekannte Wirkungskanäle, die vor allem über die Verteilung von Bildungschancen funktionieren. In Übereinstimmung hiermit zeigt sich, dass der negative Effekt der Ungleichheit bei hohen staatlichen Bildungsausgaben und bei einer hohen Kreditverfügbarkeit abgemildert wird. In hochentwickelten Volkswirtschaften ist der Wachstumseffekt der Ungleichheit außerdem insignifikant, was wahrscheinlich mit einer überdurchschnittlichen Qualität und Quantität der öffentlichen Güter, wie etwa der meist frei verfügbaren Schuldbildung, erklärt werden kann. Die staatliche Umverteilung scheint ihre Wachstumsauswirkung dagegen insbesondere über geringere private Investitionen und höhere Geburtenraten zu entfalten.

Obwohl das vierte Kapitel für hochentwickelte Volkswirtschaften keine direkten Hinweise auf eine bisherige Beeinträchtigung des Wirtschaftswachstums aufgrund der gestiegenen Ungleichheit liefert, kann auf Basis des zweiten und dritten Kapitels eine potentielle Beeinträchtigung durch eine unzureichende gesamtwirtschaftliche Nachfrage erahnt werden. Konkret weist diese Dissertation auf einen zwar nicht linearen, aber hoch signifikanten Zusammenhang zwischen der Einkommensverteilung und dem aggregierten Konsum hin. Während ein relativer Rückgang der Konsumnachfrage bis zur globalen Finanzkrise von 2008/09 in einigen Ländern durch eine gestiegene private Verschuldung umgangen wurde, haben in anderen Ländern höhere Exporte den Ausfall der binnenwirtschaftlichen Nachfrage kompensiert. Seit der Finanzkrise scheint jedoch eine enorm expansive Geld- und Fiskalpolitik notwendig zu sein, um die globale Nachfrage aufrecht zu erhalten.

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Chapter 1

Introduction

"Now, this kind of inequality –a level that we haven't seen since the Great Depression– hurts us all. When middle-class families can no longer afford to buy the goods and services that businesses are selling, when people are slipping out of the middle class, it drags down the entire economy from top to bottom."

(Obama, 2011)

Remarks by President Barack Obama in Osawatomie, Kansas, December 06, 2011.

1.1 Motivation, outline and summary

Questions of income distribution, and particularly the question of its macroeconomic consequences, are of pressing interest due to the substantial rise in income inequality that most advanced economies and many developing countries have witnessed since the 1980s.[1] In fact, many left-leaning politicians, such as former US President Barack Obama (see quote which prefaces this paper), subscribe to the idea that rising inequality may drag down the economy. Recently, two widely cited empirical studies of the IMF (Ostry et al., 2014) and the OECD (Cingano, 2014) have provided support for this idea by finding that inequality has a negative impact on economic growth. Moreover, prominent economists like Rhaguram Rajan (2010) and Joseph Stiglitz (2012) have suggested that the rise in income inequality in the United States was one of the causes of the 2008 financial crises. According to Ranciere et al. (2012), income distribution may even have played an important role for the sizeable current account imbalances that have emerged since the early 2000s.

In three self-contained studies, this dissertation contributes to these strands of literature by providing new insights into the macroeconomic consequences of income inequality from an international perspective. Following this introduction, which also includes a brief overview of trends in income distribution, Chapter 2 evaluates the relationship between the labor share of income and the evolution of aggregate demand. Chapter 3 analyzes the link between income inequality and aggregate saving; and Chapter 4 directly estimates the effect of inequality and public redistribution on economic growth. While the first two chapters focus on high-income countries, the third chapter deals with countries at all stages of development.

Drawing on panel data econometrics, this dissertation analyzes why macroeconomic aggregates like saving rates or GDP growth rates evolve differently in different countries and at different points in time. In doing so, it attempts to identify the impact of income distribution on this variability. In addition to the obvious advantage of more efficient, and thus more accurate, estimates due to larger datasets, panel data yields several benefits compared to sheer cross-sectional or time-series data (see e.g., Hsiao, 1985 and Verbeek,

[1] The widespread rise in inequality is documented in multiple studies, such as Morelli et al. (2015) and Alvaredo and Gasparini (2015). Dabla-Norris et al. (2015) provides a broad review of the causes and consequences of income inequality.

2012). Above all, panel analysis makes it possible to account for unobservable heterogeneity, which may bias the results from cross-sectional regressions. This is, for instance, beneficial if inequality is correlated with time-constant institutional factors that affect the evolution of the dependent variables. A potential problem of the panel structure is that error terms are typically correlated within countries; however, this can usually be resolved by the generation of cluster-robust standard errors (Wooldridge, 2002).

The panel data literature is divided into two 'worlds' that differ according to their underlying assumptions and the nature of the datasets in use. For datasets where the time dimension is rather small compared to the cross-sectional dimension, the traditional branch of panel data analysis imposes homogeneous parameters across countries and neglects the time-series properties of the variables. For panels which include few countries and many years, however, panel time-series methods are often used, as they allow for nonstationary data and heterogeneous parameters across countries (Eberhardt and Teal, 2011). This dissertation draws on both groups of panel estimators according to the nature of the dataset in the particular chapter. Utilizing a panel that covers up to 55 years but only 23 countries, Chapter 2 adopts a recently developed panel time-series estimator of Chudik and Pesaran (2015) instead of the homogeneous parameter methods that have been used in similar studies. As the panel is somewhat broader, and for most empirical specifications also considerably shorter, Chapter 3 sticks to the traditional panel data methods – pooled OLS, fixed-effects, two-stage least squares, and system GMM – that have been used in previous studies on this topic (e.g. Leigh and Posso, 2009). Finally, Chapter 3 draws on the system GMM estimator (Blundell and Bond, 1998; Arellano and Bover, 1995), which has emerged as the standard for empirical growth regressions with worldwide data (e.g. Halter et al., 2014; Ostry et al., 2014).

Barack Obama's conviction that the entire economy suffers when middle-class families can no longer afford to buy the goods and services that businesses are selling reflects the 'underconsumptionist' view, whose origin is often attributed to John Maynard Keynes (1936) but can be traced back at least as far as the early 19th century.[2] The first of its implications, namely a decrease in aggregate consumption and a rise in saving due

[2]Keynes provides a review of the history of this idea in chapter 23 of the General Theory of Employment, Interest and Money. According to Allgoewer (2002), the Genevan Economist Jean Charles Leonard de Sismondi (1773-1842) was one of the first who has seen income distribution as a cause of underconsumption.

to a growing concentration of income, is empirically tested in Chapters 2 and 3 of this dissertation. In addition to their consequences for the evolution of aggregate demand and ultimately of economic growth, the consumption and saving effects of income distribution may further be important for understanding the pattern of global current account imbalances (e.g. Ranciere et al., 2012).

Chapter 2 focuses on the distribution of income between labor and capital. Proponents of the underconsumptionist view, such as Keynes (1936) and Kalecki (1971), suggest that a deterioration of the labor income share will depress private consumption, as the marginal propensity to consume is higher from labor income than from profits. Yet, according to neo-classical arguments, lower wages also imply lower costs and higher profitability, meaning that a shrinking labor share could stimulate investment and export demand.

While the labor share of income, also called the wage share, was either fairly stable or rising in the decades immediately following World-War II, since the early 1980s it has substantially declined in most advanced economies and in many emerging markets (see Dao et al., 2017). The chapter empirically analyzes the consequences of this development for the evolution of aggregate demand in a panel of OECD countries. The main challenge of this investigation is the endogeneity of the labor share in the business cycle. Whereas the related empirical literature often simply assumes that the labor share is exogenous in the short run (e.g. Onaran and Obst, 2016), this chapter explicitly tests for the direction of Granger causality between the wage share and the rate of GDP growth, yielding tentative evidence for a positive two-way Granger causation.

However, the primary focus of the chapter is on the long-run relationship between the wage share and the composition of aggregate demand that has been neglected in earlier studies. By applying recently developed panel time-series methods, the chapter estimates error correction models to separate long-run cointegration relationships from possibly spurious business cycle variations. In addition to distinguishing between different time horizons, this approach accounts for parameter heterogeneity and cross-section dependence across countries.

The chapter confirms the underconsumptionist logic by showing that a shift of income from labor to capital is generally associated with a lower private consumption to GDP ratio. However, it also shows that a decreasing wage share has historically often been related to higher business investment, but that during recent decades, a decrease in the wage share was more likely to be associated with rising net exports. Combined with a substantial heterogeneity of the estimated effects and the diversity of the evolution of the wage share within different countries, this could be one explanation for the global trade and current account imbalances that have emerged since the early 2000s. However, the heterogeneous consumption effects also hint at different distributions of labor income, indicating that the labor share may be too crude an instrument for measuring income distribution.

Chapter 3 of this dissertation digs deeper into the consequences of differential consumption propensities. By focusing on the distribution of income across households and the household saving rate, it focuses on saving differentials between households at different steps of the income ladder rather than on the differences between labor and capital. In fact, the influence of income distribution on aggregate saving is ambiguous due to opposing effects at the microeconomic level that may be offsetting in the macroeconomic aggregate. On the one hand, wealthier households tend to have a higher propensity to save than households at the lower end of the income distribution (e.g. Dynan et al., 2004), such that an increasing concentration of income may cause an increase in aggregate saving. On the other hand, several micro-econometric studies find that middle- and low-income earners lower their saving rate in response to rising top incomes (e.g. Bertrand and Morse, 2016), which is why an increase in inequality could also lead to a decline in saving (e.g. Frank et al., 2014). As both mechanisms are backed by empirical evidence at the household level, the overall impact of income distribution must be assessed via country-level data. However, earlier cross-country and panel data studies have often provided inconclusive results (e.g. Li and Zou, 2004; Leigh and Posso, 2009), which could be due to the use of narrow samples, inconsistent data, or the neglect of important covariates.

By taking advantage of recent advances in data availability, particularly the increased availability of consistent Gini coefficients in the Luxembourg Income Study and the Standardized World Income Inequality Database (SWIID), the chapter sheds new light on the link between inequality and saving in advanced economies. Furthermore, it contributes to the literature by testing for various non-linearities and by accounting for new covariates like house prices and credit availability. Surprisingly, the chapter documents a robust and highly significant hump-shaped relationship between inequality and the aggregate household saving rate. At a low level of inequality, greater inequality is associated with higher saving, but when inequality is high, a negative relationship between inequality and saving prevails. The turning-point where the marginal effect of inequality changes from positive to negative is located at a net income Gini coefficient of around 30. Moreover, it appears that the relationship between inequality and saving also depends on financial market conditions: while inequality increases saving when credit is scarce, it tends to reduce saving at high levels of credit availability.

The chapter primarily focuses on household saving in order to better identify the effect of interpersonal income distribution, however - from a policy perspective - it is important to note that it also yields evidence for a non-monotonic effect of inequality on national saving and the current account balance. Although inequality may not be the main driver, in many cases the current pattern of global imbalances corresponds quite consistently with the hump-shaped relationship between inequality and saving. In fact, since the 1980s surplus countries such as Germany or Sweden have experienced a rise in inequality from initially low levels, while in several deficit countries, like the US or the UK, inequality has increased from much higher initial levels.

Chapter 4 attempts to directly address the question of whether an increase in income inequality drags down the economy. In fact, in addition to demand-side effects such as those identified in the underconsumption theory, the economic literature has found numerous reasons why inequality may affect economic growth via supply-side channels. For instance, as income inequality is closely related to unequal opportunities (Corak, 2013), it may lead to a waste of talent due to insufficient human capital investment (Galor and Zeira, 1993). As a source of social dissatisfaction, higher inequality may also result in political instability that deters investment, or in populist policies that harm economic growth (e.g. Alesina and Perotti, 1996). Public redistribution, however, is also widely regarded as harmful for growth because of disincentives and inefficiencies that accompany taxes and transfers (Okun, 1975). Comparable to the studies of Ostry et al. (2014) and Cingano (2014), Chapter 4 builds on a vast but rather inconclusive literature that analyzes the effect of income inequality on GDP growth along these aforementioned lines of reasoning.

The findings of this chapter are derived from system GMM growth regressions which are conducted in a panel of up to 154 economies at different stages of development. An innovative approach of this chapter is the application of a novel variable that measures public redistribution via taxes and transfers based on the difference between market income and net income Gini coefficients. Together with Ostry et al. (2014) and Thewissen (2014), it is thus one of the first studies that estimates the growth effects of public redistribution in this way while simultaneously estimating the influence of net income inequality on GDP growth. In addition, this chapter extends the literature by analyzing the transmission channels of inequality and redistribution, as well as by accounting for interactions between inequality and the credit to GDP ratio, the level of public spending on education, and the development level. As in Ostry et al. (2014), the inequality data is drawn from the SWIID database. However, owing to the release of an updated version of the SWIID, this dissertation benefits from even more consistent data, and it is able to employ a novel method to account for the remaining data uncertainty within the regression results.

For the worldwide sample, the chapter finds that a high level of inequality reduces GDP growth; but in contrast to the insignificant effect found in Ostry et al. (2014), it also suggests that public redistribution is negatively related to growth if inequality is held constant. Combined with its positive effect through lower inequality of net incomes, however, the full impact of redistribution is still found to be insignificant. The negative growth effect of inequality is traced back to lower education levels and higher fertility rates. Public redistribution appears to hamper growth via lower investment and increased fertility rates. Furthermore, the chapter finds that both a higher level of private credit and higher public education spending attenuate the negative effects of income inequality. Finally, the influence of inequality and public redistribution changes with the development level. A negative impact of inequality prevails in the global sample and in the group of developing and middle-income countries. Yet, contrary to the findings of Ostry et al. (2014) and Cingano (2014) but in line with other previous studies (e.g. Barro, 2000; Castelló-Climent, 2010), the effect of inequality is found to be insignificant in high-income countries.

At first glance, this dissertation thus appears to provide little evidence for the idea that rising income inequality drags down the economy in high-income countries like the United States or Germany. In addition, the results presented in Chapter 4 also conflict with demand-side explanations such as the underconsumption argument in finding that the influence of inequality vanishes when the education level and the fertility rate are held constant in growth regressions. Thus, the negative effect of inequality appears to stem from the link between unequal opportunities and human capital, a link which is weakened by a superior provision of public goods in high-income countries.

Yet, with regard to the relationship between functional income distribution and the composition of aggregate demand in Chapter 2, or between income inequality and aggregate saving in Chapter 3, the thesis provides evidence for an underconsumptionist effect in high-income countries. In fact, the parameter heterogeneity of Chapter 2, as well as the non-linearities of Chapter 3, may be reasons why a rather broad-based decline in the labor share and a widespread increase in inequality did not lead to insufficient private demand until the global financial crisis of 2008. More precisely, in many economies net exports appear to have compensated for the relative decline of consumption in GDP that was associated with a shrinking labor share. Moreover, an expansion of credit to the private sector and a high initial level of inequality seem to have altered the link between inequality and saving in countries like the USA, such that a lack of domestic demand in countries like Germany has been compensated for at a global level. Meanwhile, sizeable current account imbalances have emerged due to the diverging demand regimes.

Even more important for the maintenance of global demand may have been monetary or fiscal policy reactions, which are difficult to account for in growth regressions due to the fact that they are endogenous to the state of the economy. If, as argued by Summers (2015), the secular decline in global real interest rates (e.g. King and Low, 2014) and the sluggish recovery from the global financial crisis reflect a chronic lack of aggregate demand, this dissertation shows that some of the demand deficiency may stem from a widespread increase in income inequality.

The results of this dissertation advise some scope of action with regard to economic policy: First of all, Chapter 4 shows that generous public spending on education mitigates the negative growth effect of inequality, even if it does not directly reduce inequality itself. In the long run, however, governments should be able to simultaneously promote equity and economic efficiency by providing free and high-quality education for poorer families. Second, and somewhat more surprisingly, this dissertation also finds that altogether public redistribution via taxes and transfers is beneficial for growth in developing countries and neutral or at least not very harmful for the economic performance of high-income countries. While the identification of specific policy instruments for growth-friendly redistribution is not the goal of this dissertation, its findings imply that many governments have found ways to balance income distribution while avoiding overly negative incentive effects. The identification of these policies is certainly an important path for future economic research. It has, for instance, just been explored in the IMF's Fiscal Monitor of October 2017.[3]

1.2 Trends in income distribution

A brief overview of global trends in income distribution may be helpful as a background for the empirical analysis of this dissertation. To begin with, the following chapter will focus on the functional distribution of income between labor and capital, which is measured via the labor share, or the wage share in other words. Whereas economists have long assumed that the functional income distribution is stable in the long-run (e.g. Kaldor, 1957), recent studies have documented that labor shares have in fact declined in most advanced economies and in the majority of developing countries since the early 1980s (e.g. Dao et al., 2017). As shown in Figure 1.1, the labor share has also trended down in 17 of the 23 high-income OECD countries that are analyzed in Chapter 2. Yet the evolution of the labor share is quite heterogeneous with regard to different magnitudes of the trends and different timings of the developments. Of the five largest OECD countries, for instance, the United States and Germany have witnessed a more or less permanent decline from the 1980s until just prior to the great recession. In Italy and the United Kingdom, however, labor shares started to fall somewhat earlier, but have later moved upward or sideward over the past fifteen to twenty years.

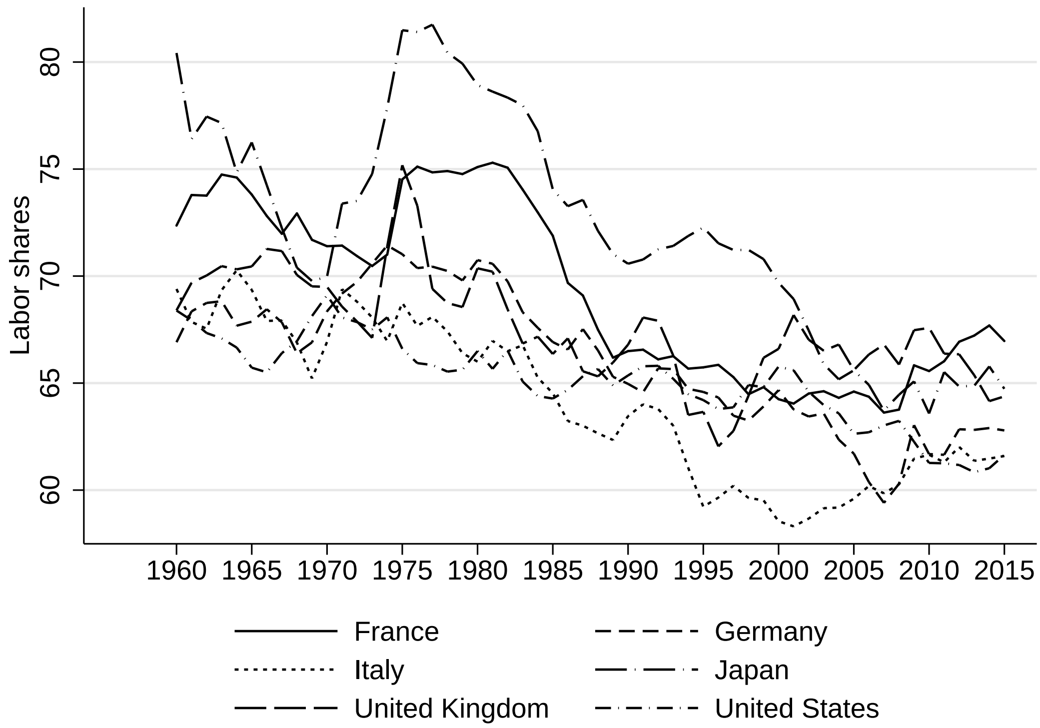
In line with most previous studies about inequality and macroeconomics, the subsequent Chapters 3 and 4 are concerned with the distribution of income across households. Among the different measures of inequality, the Gini coefficient is the most comprehensive as it takes the entire distribution of income into account.[4] Since the Gini is also by far the most established and most widely available indicator, it is the main measure of choice for multi-country panel data studies. Specifically, this dissertation foremost utilizes Ginis of net incomes from the Standardized World Income Inequality Database (SWIID), whose benefits and drawbacks will be extensively described in the respective chapters.

[3] International Monetary Fund (IMF), 2017. Fiscal Monitor: Tackling Inequality. Washington (DC).

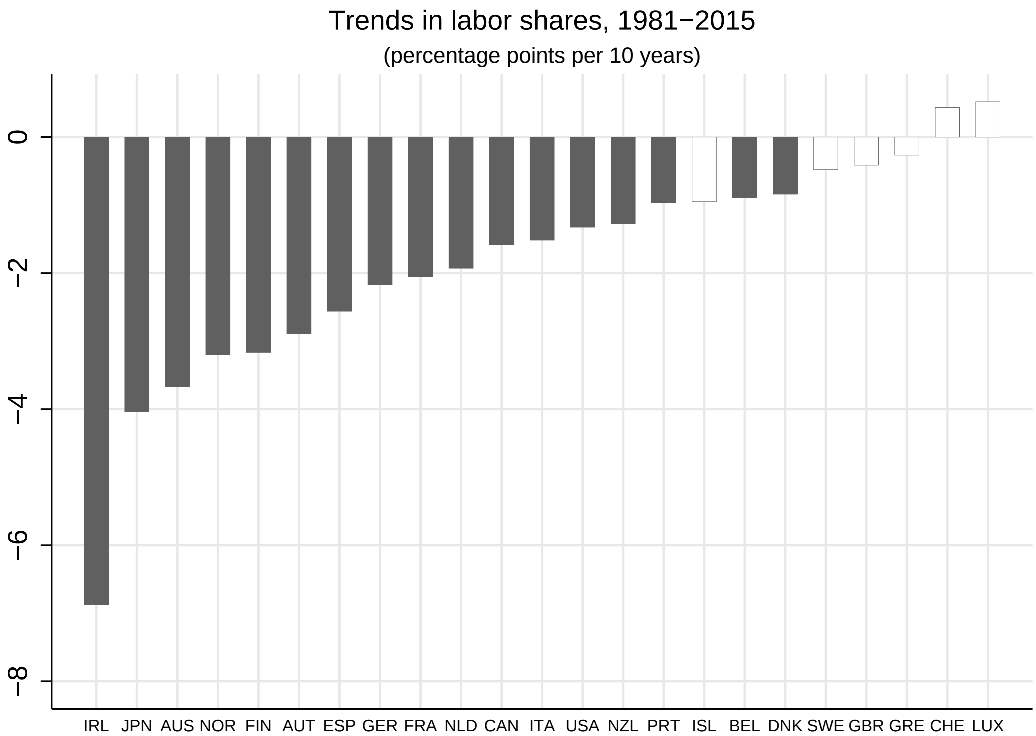
[4] A comprehensive discussion of multiple issues concerning the measurement of inequality can be found in Morelli et al. (2015).

The Ginis of the six largest industrial countries, presented in Figure 1.2, reveal an almost universal upward trend in inequality since the late 1980s, except for France, where inequality has just started to rise in the early 2000s.[5] In the six largest emerging markets, however, the evolution of inequality is much more diverse, with rapid increases in inequality within the former communist countries China and Russia, a mild increase in India, but stable or rather downward trending levels in Korea, Brazil and Mexico. Figure 1.3 provides a wider picture by showing trends in Gini coefficients within each of the 40 largest economies over the period 1981 to 2013. Here, the SWIID data indicates significant upward trends in inequality within 24 countries, whereas it shows downward trends in only 10 economies. Finally, Figure 1.4 provides an impression about the cross-country variations of inequality, which are utilized, for instance, in the system GMM estimations of Chapter 4. Regarding current levels of inequality, China and India appear to be located among the world's most unequal countries with Ginis larger than 50. While the highest inequality levels are in general observed in Africa and Latin America, small Northern- and Central European states such as Sweden, Norway, Iceland and the Czech Republic are the world's most equal countries with Ginis of about 25.

[5]Inequality data is not very reliable for earlier years, which is why data from the 1960s and 1970s is dismissed in several applications of the following chapters.

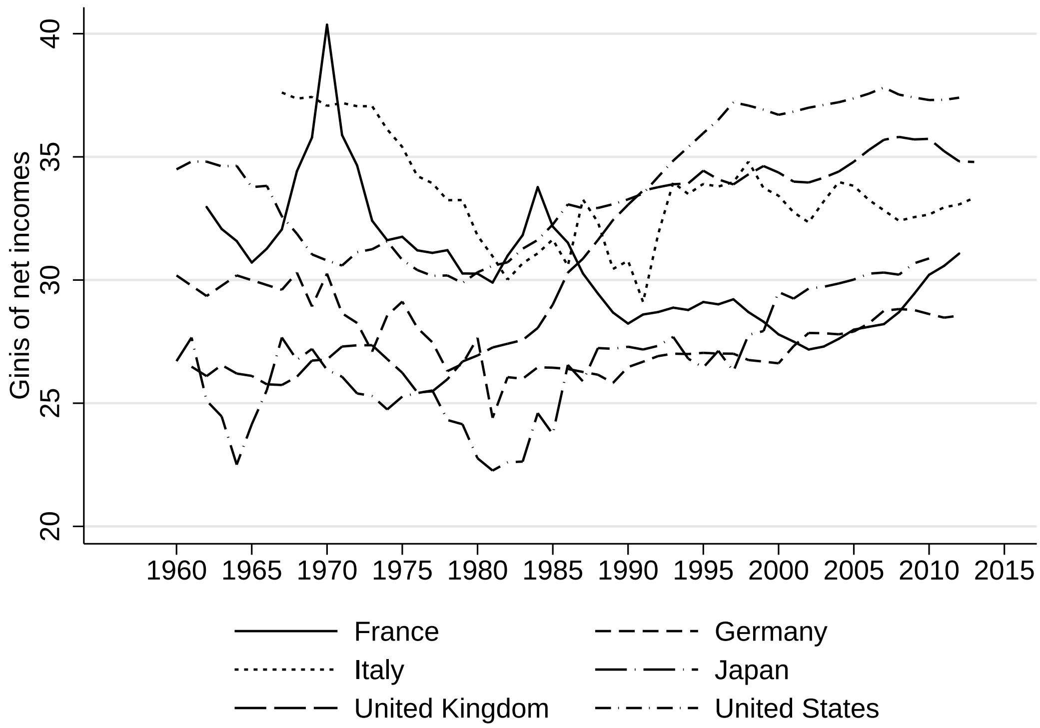


(a)

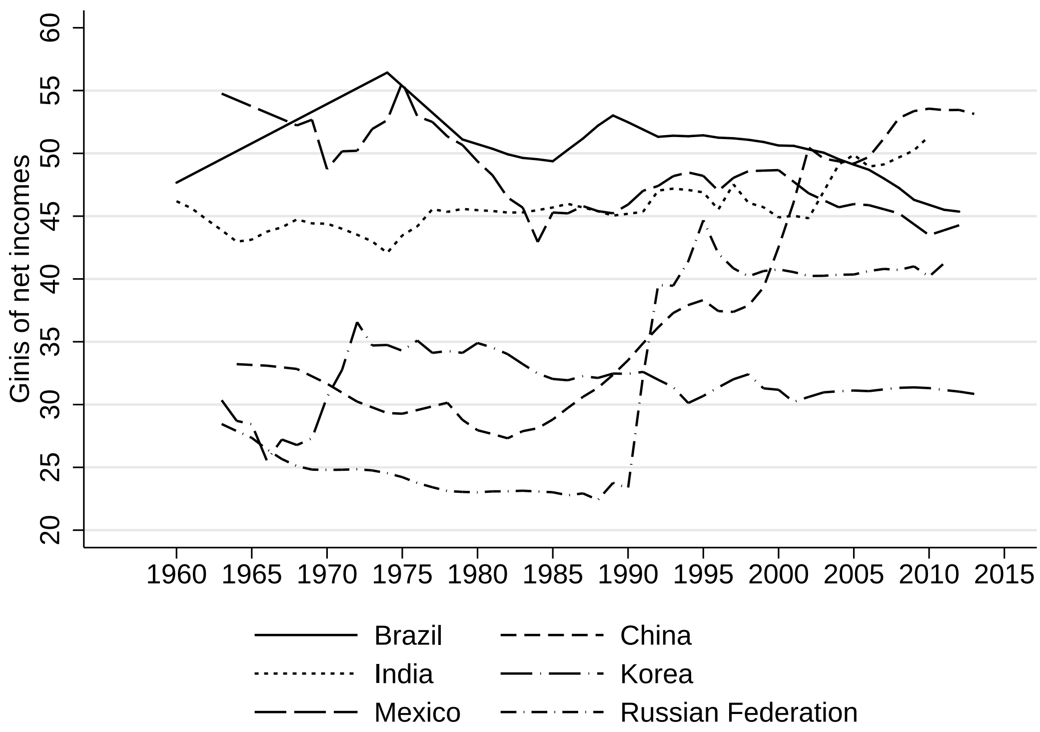


(b)

Figure 1.1: (a) Evolution of the labor income share in the six largest industrial countries. (b) Estimated trends in labor shares within 23 OECD countries.
Note: Trends are calculated for the period 1981-2015. Insignificant trends are left blank.
Source: AMECO database and own calculations.



(a)



(b)

Figure 1.2: Evolution of income inequality in the (a) six largest industrial countries and (b) six largest emerging markets.
Note: Inequality is measured via Gini coefficients of incomes net of taxes and transfers.
Source: SWIID database version 5.0.

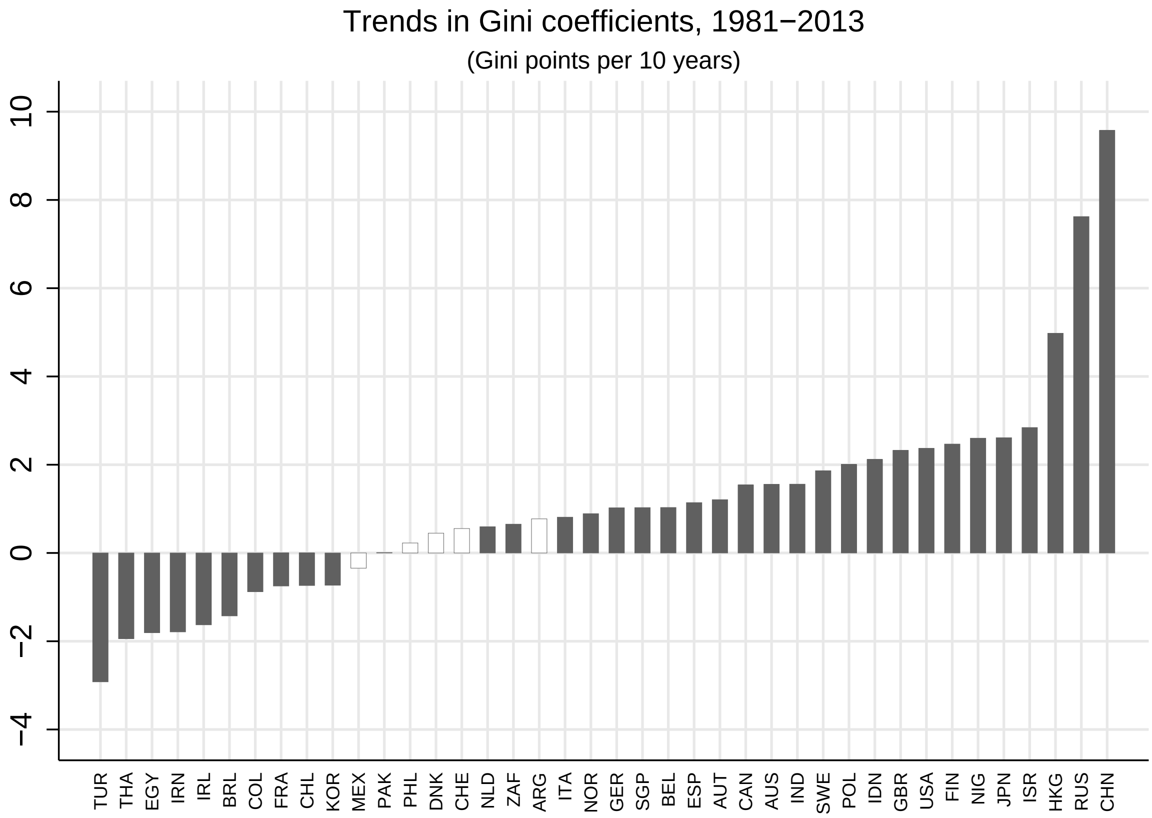


Figure 1.3: Estimated trends in Gini coefficients within the 40 largest economies.
Note: Inequality is measured via Ginis of incomes net of taxes and transfers. Trends are calculated for the period 1981-2013. For several countries no inequality data is available at the beginning or at the end of the period, so that trends are based on the maximum available time span. Insignificant trends are left blank.
Source: SWIID database version 5.0 and own calculations.

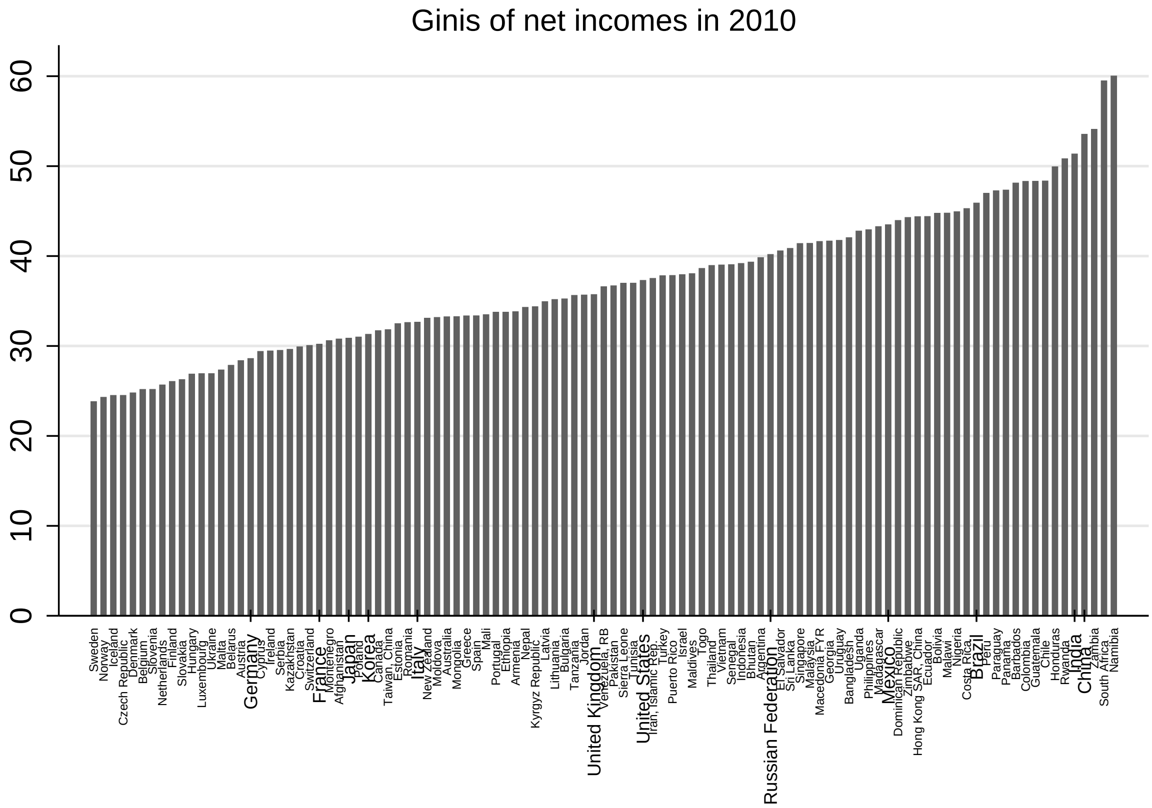


Figure 1.4: Ginis of net incomes (net of taxes and transfers), as observed in 2010.
Note: The six largest industrial countries and emerging markets are highlighted
Source: SWIID database version 5.0.

Chapter 2

The Wage Share and Aggregate Demand: Evidence from Panel Time-Series Regressions

2.1 Introduction

It is well documented that the labor share of income has substantially declined in most advanced economies since the early 1980s. Yet, while the drivers of this development have recently received much attention (e.g. Dao et al., 2017, Autor et al., 2017, Karabarbounis and Neiman, 2014), the mainstream economic literature has thus far neglected its consequences for the evolution of aggregate demand and GDP growth.[1]

Post-Keynesian and post-Kaleckian economists, however, have always been aware of the demand effects of income distribution between labor and capital. The theoretical backbone of the post-Keynesian literature is the Bhaduri and Marglin (1990) model, which summarizes the effects of a shift in the functional income distribution on the components of private demand. Following the 'underconsumptionist' view of Keynes (1936) and Kalecki (1971), the model assumes that a shrinking wage share will depress private consumption, because the propensity to consume from profits is lower than the propensity to consume from wages. Yet, since lower wages imply lower costs and higher profitability, a shrinking wage share also stimulates investment and export demand. Ultimately, it remains an empirical question whether a shift of income from labor to capital will exert a drag on aggregate demand; and it is likely that effects differ from country to country.

The present chapter belongs to a small class of studies that evaluate the effects of the wage share on the components of aggregate demand using panel data (e.g. Hartwig, 2014; Stockhammer and Wildauer, 2015). We contribute to this literature by applying current panel time-series methods to identify average long-run relationships, while also accounting for the heterogeneity across different countries which is suggested by theory.

First, however, we directly estimate the short-run interactions between the wage share and economic growth. In line with recent criticism raised by Skott (2016) we suspect a bidirectional causality, which is why we perform a set of Granger (1969) causality tests to gauge its direction. Whereas simple regressions with pooled panel data yield a positive Granger causation running in both directions, a novel test for heterogeneous panel data

[1]Instead, a vast number of studies focuses on the link between interpersonal income inequality and economic growth. As capital ownership is typically concentrated at the top of the income distribution, interpersonal inequality is affected by the functional distribution of income between labor and capital. Yet the correlation between shifts in income inequality and variations in the profit or labor share is far from perfect (Dao et al., 2017), so that exploring the direct impact of a shrinking labor share is certainly worth the effort.

models by Dumitrescu and Hurlin (2012) suggests that the effect of the wage share on growth is less robust than the reverse causality.

All things considered, a direct estimation of the growth effects of functional income distribution may be overly ambitious due to the strong endogeneity of the wage share in the business cycle. Yet, assuming that the cyclical effect of GDP growth on the wage share will eventually level out, the estimation of long-run effects may be more reliable. Moreover, using the demand components individually as dependent variables will further mitigate endogeneity concerns and provide more detailed insights into the validity of the Badhuri-Marglin model. Hence, the second part of this chapter focuses on isolating the long-run connection between the wage share and the components of aggregate demand. For this exercise, cointegration relationships are distinguished from cyclical short-run effects via utilization of a dynamic mean group estimator recently developed by Chudik and Pesaran (2015). This approach combines the advantages of both time series and panel data methods by providing efficient estimations that allow for heterogeneous parameters and unobserved common factors. In accordance with the theoretical predictions, we find a positive cointegration relationship between the wage share and the ratio of private consumption to GDP, and a negative link between wages and private investment. Whereas the latter relationship seems to have vanished in the past few decades, more recently a decrease in the wage share has been related to larger net exports.

The chapter is structured as follows. The next section summarizes the Bhaduri-Margin model in order to establish the theoretical framework for the following empirical estimations. Section 2.3 details the motivation for our approach based on a review of the empirical literature. Section 2.4 analyzes the short-run relationship between the wage share and GDP growth, and Section 2.5 examines the long-run relationship with the individual demand components. Section 2.6 concludes.

2.2 The Bhaduri-Marglin model

The effect of income distribution on aggregate demand plays a major role in Keynesian economics. While mainstream models of economic growth assume that the economy is in full employment equilibrium, post-Keynesian economists assume that capacity utilization is usually below its potential. Economic growth is thus primarily driven by the evolution of aggregate demand, in the short as well as in the long run.

In further contrast to the mainstream literature on inequality and growth, post-Keynesians mainly refer to the income distribution between labor and capital – the functional income distribution – instead of the interpersonal income distribution. Based on authors like Keynes, 1936 and Kalecki, 1971, who argue that the income distribution may affect aggregate demand, Bhaduri and Marglin (1990) have established the workhorse model of this relationship. Following the Keynesian tradition, the model assumes that the propensity to consume out of wages is higher than the propensity to consume out of profits, so that a decrease in the wage share will suppress private consumption. Yet, in accordance with classical economics, the model also considers that wages constitute important costs of production, which leads to higher expected future profitability of investments and an increased competitiveness of exports after a drop in the wage share.

$$Y = C(Y, \pi) + I(Y, \pi, x_I) + NX(Y, \pi, x_{NX}) \tag{2.1}$$

Equation 2.1 summarizes these effects on aggregate demand. It shows that in the Bhaduri-Marglin model, private demand depends on exogenous variations in the profit share ($\pi = 1$ - wage share), income (Y), and some exogenous variables (x). Differentiating the demand equation with respect to the profit share yields the total effect of a change in income distribution:

$$\frac{dY}{d\pi} = \frac{\frac{\partial C}{\partial \pi} + \frac{\partial I}{\partial \pi} + \frac{\partial NX}{\partial \pi}}{1 - (\frac{\partial C}{\partial Y} + \frac{\partial I}{\partial Y} + \frac{\partial NX}{\partial Y})} \tag{2.2}$$

The partial demand effect of an increase in the profit share is assumed to be negative for consumption ($\partial C/\partial \pi < 0$) but positive for investment ($\partial I/\partial \pi > 0$) and net exports ($\partial NX/\partial \pi > 0$). For domestic demand the total effect of redistribution from labor to capital depends on the size of the consumption differential between wage earners and capitalists and on the sensitivity of investment to profits. In an open economy, the type of demand regime additionally depends on the degree of trade openness and the elasticity of net exports to unit labor costs, the latter of which is closely related to the wage share.[2]

[2]In the AMECO database, real unit labor costs are identical to the wage share at market prices.

For a closed economy, the Bhaduri-Marglin model can be clarified with an IS curve, defined according to the following equation:

$$s\pi z = I(\pi, z) \tag{2.3}$$

On the left hand side, aggregate saving is the product of the saving rate of capitalists s, the profit share of income π, and the degree of capacity utilization z.[3] The model is kept simple due to the assumption that all wages are consumed and profits are the only source of saving. On the right hand side, investment is a positive function of profits and of capacity utilization. In a z, π-space, the slope of the IS curve is negative when capital owners' propensity to save is high and investments are more sensitive to capacity utilization than to the profit share. As an increase in wages at the expense of profits would thus lead to a rise in aggregate demand, this situation is called a *wage-led* demand regime. Conversely, when capitalists' propensity to save is low and investment reacts more strongly to increases in profitability than to variations in capacity utilization, the slope of the IS curve is positive. This constitutes a *profit-led* demand regime.

2.3 Related literature and motivation

To asses whether a demand regime is profit-led or wage-led, most post-Keynesian studies estimate the sign of the numerator of the total derivative of the demand equation from the Bhaduri-Marglin model (Equation 2.2). Usually this is achieved via the single equation approach, which means that each demand component is separately regressed on the wage share or profit share, in addition to a few control variables. The estimated partial effects are then added up to give the effect of a change in income distribution on aggregate demand: if the total effect of an increase in the wage share (or a decrease in the profit share) is positive, the demand regime is classified as *wage-led*, while it is classified as *profit-led* if the sign is negative. Interactions between the evolution of the individual demand components and a potential endogeneity of the wage share with regard to the business cycle are usually not considered.

Drawing on a literature survey by Stockhammer (2017), Figure 2.1 (in the appendix) summarizes the results of the empirical literature on demand regimes in selected coun-

[3] In the Keynesian framework of the model, the level of aggregate output depends solely on the degree of capacity utilization. Hence, capacity utilization and aggregate output are actually interchangeable, whereas Bhaduri and Marglin use only the former term.

tries.[4] Most studies find a positive correlation between the wage share and consumption, whereas the link between the wage share and investment is usually negative and somewhat weaker. Thus, based on single-country regressions and the single-equation approach, domestic demand seems to be wage-led in the majority of developed economies. The evidence is more mixed when considering total demand, as some open economies, such as Austria, are found to be wage-led when the effect of redistribution on net exports is taken into account. Yet recent studies point out that a simultaneous decline in the wage share in all countries will even lead to lower demand in most export-driven economies (Onaran and Galanis, 2014; Onaran and Obst, 2016).

In contrast to the extensive usage of time series methods in this context, only few studies apply panel data methods to analyze the link between income distribution and demand. Based on a panel of 31 OECD countries, Hartwig (2014) finds a slightly wage-led demand regime by estimating a structural model. Stockhammer and Wildauer (2015) also find a wage-led demand regime in a panel of 18 OECD countries while controlling for the influence of asset prices, debt, and income inequality.

As recently pointed out by Skott (2016), a major problem of the previously mentioned literature is the postulation of a unidirectional causality leading from distribution to aggregate demand, although research on the development of wage shares suggests a number of reasons why the functional distribution of income could be affected by the state of the economy (see, e.g. Rios-Rull and Santaeulalia-Llopis, 2010 and Schneider, 2011). For instance, during periods of economic recovery, profits typically rise faster than wages, while labor market frictions like long term contracts and job protection laws prevent companies from reducing their wage bill during a contraction. Both cause the wage share to move in a countercyclical manner, so that the identification of short-run effects via simple OLS regressions would be subject to simultaneity bias.

One way to deal with this bias is a vector autoregression (VAR) approach, which explicitly models the interactions between the functional distribution of income and some measure of aggregate demand. Based on reduced form demand equations, these studies tend to find profit-led demand regimes (e.g. Barbosa-Filho and Taylor, 2006; Kiefer and Rada, 2015) or very weak effects of income distribution (Stockhammer and Onaran, 2004). A drawback of the VAR approach is that it is difficult to evaluate the transmission of the

[4]Stockhammer and Onaran (2013) and Stockhammer (2017) provide comprehensive surveys of the empirical literature.

effects of income distribution to aggregate demand. Moreover, as a VAR model typically measures short- to medium-run effects, it may neglect the structural decline of the wage share that has occurred in many economies over the last decades.

In accordance with the majority of studies on this topic, this chapter follows the single equation approach by investigating the link between the wage share and individual demand components. However, we deviate from the literature by estimating error correction models in order to separate long-run and short-run effects in a panel of countries. The main goal of this approach is the identification of a structural relationship which can be distinguished from potentially spurious business cycle variations.[5] Moreover, we are the first to apply panel time-series methods, which enable us to quantify average effects while allowing for the parameter heterogeneity that is indicated by the rather diverse results from time series regressions. First, however, we will directly explore the short-run relationship between the wage share and economic growth in the next section. In addition to a brief review of the presumably biased contemporaneous correlations, we will focus on tests for Granger causality.

2.4 The wage share and economic growth: Short-run correlations and Granger casuality

2.4.1 Data and estimation procedure

Our panel consists of annual observations from 23 OECD countries which we selected by removing transition economies from the group of high-income OECD countries. The data covers the years from 1961 to 2015 and is mainly drawn from the European Commission's AMECO database and the OECD. Table 2.1 provides descriptions and summary statistics for all variables.

Ideally, a problem of unclear causality may be solved by the application of instrumental variable methods. Yet Bazzi and Clemens (2013) point out that external instruments are often invalid due to a violation of the exclusion restriction.[6] The application of internal

[5] Our analysis rests on the assumption that in the long run, the wage share is exogenous with regard to the composition of GDP. This assumption would be consistent with several explanations for the decline in the wage share, i.e. with technological change, labor market liberalization, the deterioration of workers' bargaining power, and also with the rise of superstar firms as recently suggested by Autor et al. (2017).

[6] Ignoring the exclusion restriction for a moment, we attempted to use unionization (the ratio of

Table 2.1: Data description for Section 2.4

Variable	Description	Source	Mean	Std. Dev.	Min	Max
Δ ln(GDP)	Gross domestic product at constant market prices (OVGD)	AMECO	0.0291	0.0277	-.0958	0.233
Δ ln(WS)	Adjusted wage share as % of GDP (ALCD2)	AMECO	-0.0019	0.0261	-0.144	0.221
Δ ln(houses)	Real house prices index	OECD	0.0171	0.0683	-0.228	0.328
Δ ln(equities)	Main national equity index	OECD	0.0598	0.213	-2.023	1.108
Δ ln(credit)	Domestic credit to private sector as % of GDP	World Bank	0.0262	0.112	-1.003	1.353
Δ ln(gini)	Gini of net incomes	SWIID 5.0	0.002	0.0304	-0.138	0.182

Notes: Countries included are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, and the United States.

instruments via difference or system GMM estimators, which is common in panel data studies on economic growth, is also problematic because of the long time dimension and rather narrow cross-section of our panel. Thus our exploration of 'causal' short term effects is limited to tests for Granger (1969) causality. In other words, we test whether in an autoregressive model, past changes in the wage share predict current rates of GDP growth (Equation 2.4); and we compare the results with those regarding the predictive power of past GDP growth rates for current wage shares (Equation 2.5):

$$\Delta\ln(\mathrm{GDP})_{it} = \sum_{k=1}^{K} \beta_{ik}\Delta\ln(\mathrm{GDP})_{i,t-k} + \sum_{k=1}^{K} \gamma_{ik}\Delta\ln(\mathrm{WS})_{i,t-k} + \alpha_i + \epsilon_{it} \tag{2.4}$$

$$\Delta\ln(\mathrm{WS})_{it} = \sum_{k=1}^{K} \beta_{ik}\Delta\ln(\mathrm{WS})_{i,t-k} + \sum_{k=1}^{K} \gamma_{ik}\Delta\ln(\mathrm{GDP})_{i,t-k} + \alpha_i + \epsilon_{it} \tag{2.5}$$

Whereas Granger causality should not be seen as sufficient evidence for a direct causal effect of the wage share on economic growth, it still can serve as a plausibility check for such an effect based on the principle that the past determines the future. To test for Granger causality we apply two different approaches with regard to the assumptions about the constancy of model parameters across countries. Assuming that the parameters are homogeneous (β_i=β and γ_i=γ), we start with simple regressions based on the pooled panel data. In this case, Granger causality is assessed based on an F-test for the joint significance of the parameters γ_k or based on t-tests in models that include only one

union membership to employment) from Madsen and Ang (2016) as an instrument for the wage share. Yet unionization constitutes a surprisingly weak instrument in our case, so that we did not proceed on this path.

lag of the explanatory variables. Next, however, parameters are allowed to differ across countries (i = 1,...,N) and inferences about Granger causality are computed according to the approach of Dumitrescu and Hurlin (2012).[7] Whereas the former approach conducts a test of homogeneous non-causality against the alternative hypothesis of Granger causality everywhere in the panel, the latter approach of Dumitrescu and Hurlin tests the null hypothesis of non-causality against the alternative of Granger causality for at least one country in the sample.

2.4.2 Results

Table 2.2 presents the results from pooled panel data regressions with all variables provided as first differences. In Column (1) we regress GDP growth on contemporaneous variations in wage shares (WS), asset prices (houses and equities), interest rates (interest), personal inequality (gini), and the private credit to GDP ratio (credit), roughly replicating the models used by Stockhammer and Wildauer (2015) for explanations of private consumption and investment. Here, the principal problem with the estimation of contemporaneous short-run correlations becomes obvious. In contrast to the wage-led demand regime in Stockhammer and Wildauer (2015), our results point towards profit-led demand due to the identified negative correlation between the wage share and economic growth. The direction of causality, however, is entirely unclear. As profits are more flexible than wages in the short run, the countercyclical movements of the wage share may be caused by economic growth rather than the other way round.

To gauge the direction of causality, Columns (2)-(7) present the results from Granger (1969) causality tests using the pooled data and assuming homogeneous parameters. The even numbered columns show the correlations of current GDP growth with the lagged wage share, while the odd numbered columns present the correlations between the wage share and lagged GDP growth. Columns (2) and (3) present simple OLS regressions. In Columns (4) and (5), the lagged dependent variable is instrumented by its third and fourth lagged levels to deal with a potential dynamic panel problem (see Anderson and Hsiao, 1982; Arellano, 1989).[8] In addition, Columns (6) and (7) reintroduce the control

[7]Dumitrescu and Hurlin (2012) suggest to run separate regressions for each country before averaging the Wald statistics and computing a standardized Z statistic.The procedure is incorporated in Stata via the xtgcause command by Lopez and Weber (2017).

[8]As the Arellano-Bond test detects first- and second-order autocorrelation, we do not use the second lag as an instrument.

Table 2.2: Short-run correlations and Granger causality regressions with pooled panel data

	(1) Δ ln(GDP)	(2) Δ ln(GDP)	(3) Δ ln(WS)	(4) Δ ln(GDP)	(5) Δ ln(WS)	(6) Δ ln(GDP)	(7) Δ ln(WS)
Δ ln(WS)	-0.322***						
	(0.0601)						
Δ ln(GDP)$_{t-1}$		0.774***	0.0467**	0.864***	0.287***	0.997***	0.384***
		(0.0243)	(0.0199)	(0.101)	(0.0677)	(0.228)	(0.0643)
Δ ln(WS)$_{t-1}$		0.117**	0.132***	0.0851*	0.604***	0.187**	0.781***
		(0.0544)	(0.0389)	(0.0509)	(0.0958)	(0.0735)	(0.207)
Δ ln(houses)	0.202***						
	(0.0183)						
Δ ln(equities)	0.0505***						
	(0.00416)						
Δ ln(credit)	0.0231**						
	(0.0104)						
Δ ln(gini)	0.00946						
	(0.0353)						
Δ ln(houses)$_{t-1}$						-0.0869**	-0.00617
						(0.0341)	(0.0251)
Δ ln(equities)$_{t-1}$						0.0107*	-0.00458
						(0.00648)	(0.0221)
Δ ln(credit)$_{t-1}$						0.00102	-0.000657
						(0.00553)	(0.00707)
Δ ln(gini)$_{t-1}$						-0.00776	-0.0344
						(0.0184)	(0.0350)
time dummies	No	No	No	Yes	Yes	Yes	Yes
Observations	677	1175	1173	1135	1127	677	673
Countries	23	23	23	23	23	23	23

Notes: Cluster robust, i.e. autocorrelation- and heteroskedasticity-robust standard errors are given in parentheses. Columns (1)-(3) report simple OLS regressions. In Columns (4) to (7) the lagged dependent variables are instrumented by their own lags in levels. As Arellano-Bond tests detect second-order autocorrelation of the error term, the third and the fourth lags are applied as instruments.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

variables from Stockhammer and Wildauer (2015), which are now also lagged by one time period. Aside from the simple OLS regressions, all models include time dummies in order to capture common shocks.

Regardless of the specific regression model employed, the results in Columns (2)-(7) suggest that shifts in income distribution and economic growth mutually influence each other: The growth regressions indicate a positive effect of past variations in the wage share on current growth rates, and past growth is also associated with an increase in the current wage share. Taken at face value, these results suggest a wage-led demand regime, as a rising wage share may trigger a virtuous circle of higher growth rates and higher wages. Yet the finding of a negative contemporaneous correlation combined with that of a positive correlation between lagged growth rates and current wage shares also provides evidence that a delayed reaction of wages in the business cycle may be the reason for countercyclical variations in the wage share.

Table 2.3: Granger causality tests with homogeneous versus heterogeneous parameters

	Pooled data (homogeneous parameters)			Dumitrescu and Hurlin (2012) (heterogeneous parameters)		
No. of lags		WS $\rightarrow$ GDP	GDP $\rightarrow$ WS		WS $\rightarrow$ GDP	GDP $\rightarrow$ WS
1/AIC/BIC	F-Stat.	9.81	7.53	Zbar-Stat.	2.161	18.518
	(p-value)	(0.0055)	(0.0129)	(p-value)	(0.0307)	(0.000)
2	F-Stat.	3.04	2.74	Zbar-Stat.	0.692	14.126
	(p-value)	(0.0713)	(0.0898)	(p-value)	(0.489)	(0.000)
3	F-Stat.	2.67	4.18	Zbar-Stat.	0.655	13.219
	(p-value)	(0.0772)	(0.0197)	(p-value)	(0.512)	(0.000)

Notes: The left panel presents pooled Granger causality tests, while the right panel exhibits Dumitrescu and Hurlin (2012) Granger causality tests, performed via the *xtgcause* command from Lopez and Weber (2017). As the Dumitrescu and Hurlin tests require a balanced panel, data from Israel, New Zealand, Switzerland, and Iceland is removed from the sample and the panel ends in 2014. WS $\rightarrow$ GDP denotes Granger causality from $\Delta\ \ln(\mathrm{WS})_{t-k}$ to $\Delta\ \ln(\mathrm{GDP})$, which in cases with homogeneous parameters is evaluated via F-tests on the coefficient(s) γ_k from Equations 2.4 and 2.5. In the Dumitrescu and Hurlin case Zbar-statistics are reported, as the time dimension of the panel is sufficiently large. The optimal number of lags according to the Akaike/Bayesian information criterion (AIC/BIC) is always 1.

Table 2.3 presents the results from the Dumitrescu and Hurlin (2012) test for Granger causality in heterogeneous parameter models. When we apply the Akaike or Bayesian information criterion, the optimal number of lags is one and a bidirectional Granger causality emerges. Yet when additional lags are used, causality only runs from GDP to the wage share, and not in the opposite direction. Similarly, in the homogeneous parameter models shown in the left panel of Table 2.3, Granger causation from the wage share to GDP growth becomes somewhat less significant when the number of lags is larger than one.

Taken together, for our group of high-income OECD countries the tests indicate a bidirectional Granger causation between economic growth and the wage share. However, as this result is not fully robust to the assumption of parameter heterogeneity and to larger numbers of lags in the models, the evidence for a distinct effect of the wage share on GDP growth is rather mixed. Hence, the remainder of this chapter will focus on long-run effects and individual demand components.

2.5 The wage share and the composition of demand: Long-run effects

2.5.1 Data and empirical specification

In line with the standard practice in the post-Keynesian literature, this section applies the single equation approach by separately estimating the relationship between the wage share and the components of private demand, i.e. private consumption, investment, and net exports. However, as the Bhaduri-Marglin model solely relates to business investment, we subtract residential investments from the amount of gross fixed capital formation and add it to private final consumption expenditure.[9] Moreover, we divide the demand components by GDP in order to obtain variables with statistical properties similar to those of the wage share. Table 2.4 provides further descriptions, sources, and summary statistics for all variables. With regard to the stationarity of the data, the results of panel unit root tests (in the Appendix) are inconclusive, calling for a flexible approach that is able to incorporate different time-series properties and cointegration relationships in different countries (see Eberhardt and Teal, 2011 and Yamarik et al., 2016).[10]

We identify the long-run and short-run effects of the wage share by estimating an error correction model:

$$\Delta \mathrm{C/Y}_{it} = \rho_i(\mathrm{C/Y}_{i,t-1} - \beta_i \mathrm{WS}_{i,t-1}) + \gamma_i \Delta \mathrm{WS}_{i,t} + \alpha_i + \lambda_{i'} f_t + \epsilon_{it}, \tag{2.6}$$

where i= 1,..., 23 denote countries and t = 1961,...,2015 denote years. C/Y is the ratio of private consumption to GDP, on which we focus for the presentation of the empirical specification.[11] WS stands for the adjusted wage share. ρ_i is the error correction term. β_i and γ_i denote long-run and short-run effects, respectively. In contrast to pooled panel data analysis, the parameters are allowed to differ across countries. As we assume that short-

[9] Results for estimations with standard consumption and investment variables are qualitatively similar and available upon request.

[10] We conducted panel unit root tests according to Maddala and Wu (1999) and Pesaran (2007) with a variety of lag augmentations in the Dickey Fuller regressions. For all variables, except for the credit to GDP ratio, the null hypothesis that all country series contain unit roots is rejected in at least one of the specifications. Hence, we may assume that the variables are non-stationary in many but not all of the countries.

[11] The empirical approach is identical for regressions of investment to GDP and net exports to GDP.

Table 2.4: Data description for Section 2.5

Variable	Description	Source	Mean	Std. Dev.	Min	Max
C/Y	[(Private final consumption expenditure (UCPH) + Gross fixed capital formation: dwellings (UIGDW)) ÷ GDP (UVGD)]*100	AMECO	61.688	7.650	33.312	85.796
I/Y	[(Gross fixed capital formation (UIGT) - Gross fixed capital formation: dwellings (UIGDW)) ÷ GDP (UVGD)]*100	AMECO	17.565	3.443	7.884	30.811
(NX)/Y	[(Exports of goods and services (UXGS) - Imports of goods and services (UMGS)) ÷ GDP (UVGD)]*100	AMECO	1.455	6.546	-17.188	34.697
WS	Adjusted wage share as % of GDP (ALCD2)	AMECO	65.633	5.978	45.252	93.877
credit	Domestic credit to private sector as % of GDP	World Bank	83.332	45.570	12.133	311.063

Notes: Countries included are Australia, Austria, Belgium, Canada , Denmark, Finland, France, Germany, Greece , Iceland, Ireland, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom, and the United States.

run effects are subject to a simultaneity bias, our focus is on the long-run cointegration relationship, given in parentheses. α_i captures country fixed-effects.

Our preferred technique for estimating this error correction model is the dynamic common correlated effects (DCCE) mean group estimator of Pesaran (2006) and Chudik and Pesaran (2015). The DCCE estimator incorporates a set of unobserved common factors with heterogeneous impacts ($\lambda_i f_t$) in order to control for latent drivers of the economy. If ignored, the latter can produce cross-section dependence in the regression errors, which can lead to incorrect inferences (Eberhardt and Teal, 2011).[12] In contrast, the standard Pesaran and Smith (1995) mean group (MG) estimator ignores the time-variant unobservables, but we replace them by introducing country-specific linear trends.

Following the groundwork laid by Chudik and Pesaran (2015) and its application by Eberhardt and Presbitero (2015), Equation 2.6 can be reparameterized and augmented to implement the DCCE estimator via the following regression equation:

$$\begin{aligned}\Delta \mathrm{C/Y}_{it} = \alpha_i + \pi_i^{EC}\mathrm{C/Y}_{i,t-1} + \pi_i^{WS}\mathrm{WS}_{i,t-1} + \pi_i^{ws}\Delta\mathrm{WS}_{i,t} \\ +\pi_{1i}^{T}\overline{\mathrm{C/Y}_{t-1}} + \pi_{2i}^{T}\overline{\Delta\mathrm{C/Y}_{t}} + \pi_{3i}^{T}\overline{\mathrm{WS}_{t-1}} + \pi_{4i}^{T}\overline{\Delta\mathrm{WS}_{t}} \\ + \sum \pi_{5i}^{T}\overline{\Delta\mathrm{C/Y}_{t-l}} + \sum \pi_{6i}^{T}\overline{\Delta\mathrm{WS}_{t-l}} + \epsilon_{it}\end{aligned} \tag{2.7}$$

[12]The common factors can be strong factors, like the great recession of the late 2000s; and weak factors, which are limited to certain groups of countries. The model incorporates long- and short-run effects of f_t.

Based on Equation 2.7, the long-run coefficient of the wage share can be calculated as $\beta_i = -\pi_i^{WS}/\pi_i^{EC}$, whereas the parameter π_i^{ws} directly measures the short-run relationship. Inference on π_i^{EC} indicates the presence of a long-run equilibrium relationship. The model is estimated via simple OLS and accounts for non-stationarity and cross-section dependence due to its empirical specification: The key innovation of Pesaran (2006) was the inclusion of cross-section averages (line two) to capture the unobserved common factors with heterogeneous impact. Chudik and Pesaran (2015) added several lags of the cross-section averages (line three), yielding the dynamic common correlated effects (DCCE) mean group estimator. The estimator performs well in dynamic models, even if regressors are only weakly exogenous. In other words, the approach accounts for feedback between the wage share and the consumption to GDP ratio.

2.5.2 Results

Table 2.5 presents the results for the consumption equation in Columns (1)-(3), for the investment equation in Columns (4)-(6), and for the net export equation in Columns (7)-(9). Columns (1), (4) and (7) report the results from standard two-way fixed effects regressions, which impose homogeneous parameters across all countries. All other columns feature panel time-series models, for which we report the outlier-robust means of the heterogeneous parameters (Hamilton, 1992). Among the heterogeneous estimators, Columns (2), (5) and (8) present mean group (MG) estimations with country-specific trends. Meanwhile, Columns (3), (6) and (9) feature the preferred DCCE mean group estimator, which is augmented with cross-section averages of two additional lags to capture unobserved common factors. To enhance the comparability of the estimated effects, all regressions are based on a common sample.[13]

Regardless of the particular estimator, we find a positive short-run correlation between the wage share and the consumption share. In accordance with many post-Keynesian studies, this could be interpreted as evidence to support the differential saving rates hypothesis. Yet the contemporaneous correlations may also be biased due to the countercyclical behavior of both variables.[14] Thus, it is important that a strong long-run cointegration

[13]Due to the augmentation with the lagged cross-section averages, some of the earliest observations are lost with the DCCE estimator.

[14]The countercyclicality of the consumption share may originate from the relative stability of consumption compared to investment. Reasons for the countercyclicality of the wage share were presented in Section 2.3.

Table 2.5: ECM models, panel time-series estimations, full sample 1961-2015

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dep. var.		$\Delta(C/Y)$			$\Delta(I/Y)$			$\Delta(NX/Y)$	
Estimator	2FE	MG	DCCE	2FE	MG	DCCE	2FE	MG	DCCE
EC coefficient									
$(C/Y)_{i,t-1}$	-0.0596*	-0.197***	-0.189***						
	(0.0298)	(0.0276)	(0.0305)						
$(I/Y)_{i,t-1}$				-0.151***	-0.254***	-0.276***			
				(0.0152)	(0.0245)	(0.0342)			
$(NX/Y)_{i,t-1}$							-0.115***	-0.251***	-0.286***
							(0.0279)	(0.0357)	(0.0369)
Short-run avg. coef.									
Δ WS	0.337***	0.286***	0.278***	0.123**	-0.00409	0.0159	-0.493***	-0.180***	-0.217***
	(0.0722)	(0.0447)	(0.0411)	(0.0532)	(0.0350)	(0.0342)	(0.120)	(0.0586)	(0.0463)
Long-run avg. coef.									
WS	0.190	0.332***	0.439***	-.0678	-0.444***	-0.358***	-0.438*	-0.0352	-0.157
	(0.282)	(0.122)	(0.112)	(0.120)	(0.104)	(0.121)	(0.216)	(0.156)	(0.144)
RMSE	1.17	0.997	0.844	.998	0.945	0.761	1.662	1.409	1.162
CD-stat	-3.11	3.79	-2.50	-3.01	18.08	-1.54	-3.47	8.29	-1.74
CD p-val	0.002	0.000	0.012	0.003	0.000	0.123	0.001	0.000	0.083
Observations	1089	1089	1070	1089	1089	1070	1089	1089	1070
No. of groups	23	23	23	23	23	23	23	23	23

Notes: 2FE, MG, and DCCE denote two-way fixed effects, mean group, and dynamic common correlated effects mean group estimations. The MG model is augmented with country-specific linear trends. The DCCE model includes cross-section averages of two additional lags. We report the outlier-robust means (Hamilton, 1992) of the regression coefficients for the heterogeneous parameter models. Standard errors are given in parentheses. RMSE is the root mean squared error. CD reports Pesaran (2004) CD test statistics and p-values for the null of cross-section independence. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

relationship emerges between wages and consumption when the heterogeneous estimators are applied in Columns (2) and (3). The insignificance of the long-run coefficient in the fixed effects model of Column (1) reflects differential time-series properties of the variables across countries.

For the investment to GDP ratio (I/Y), the contemporaneous effects of the wage share are mostly insignificant. However, in line with the economic mechanism of Bhaduri and Marglin (1990), the heterogeneous parameter estimators in Columns (5) and (6) yield evidence for a negative long-run relationship between wages and investment.

Finally, all of the estimators yield a negative contemporaneous correlation between the wage share and the ratio of net exports to GDP (NX/Y), while the heterogeneous estimators reject the existence of a cointegration relationship.

Quantitatively, the long-run coefficients from the DCCE estimations suggest that a decrease in the wage share by 10 percentage points is associated with an average decrease in the consumption share by roughly 4.4 pp and an average increase in the investment share by 3.6 pp. In agreement with earlier studies (e.g. Onaran and Obst, 2016), we also find that a declining wage share is associated with a contemporaneous decrease in consumption and a slightly smaller increase in net exports.

Results from cross-section dependence (CD) tests on the regression residuals (Pesaran, 2004) are reported in the bottom part of Table 2.5. In spite of all efforts to account for the unobserved common factors, the CD test statistics suggest that the null hypothesis of cross-section independence must be rejected in most cases.[15] However, use of the DCCE estimator does at least reduce the presence of cross-section dependence, and such yields the most reliable results when compared to the alternative estimation strategies.

Robustness

So far, all estimations cover the maximum available time period, which extents from 1961 to 2015. However, it may be worthwhile to focus on the more recent data, which may be more meaningful for evaluating the consequences of future shifts in income distribution. Thus, we repeat the baseline DCCE estimations for the sub-period 1991-2015. This time period was chosen to capture the acceleration in globalization that began with the fall of

[15] The introduction of further cross-sectional averages (third and fourth lags) was also not successful in mitigating the remaining cross-section dependence. Results for regressions with these augmentations are available upon request.

the iron curtain and the entry of China and India into the world economy.[16] While the selection of the sub-period eliminates about half of all observations, the reduced sample is still large enough to allow for efficient estimations.

Table 2.6 presents the regression results. Columns (1)-(3) suggest that recently, the positive link between the wage share and consumption to GDP has been maintained, and has even increased somewhat compared to the full sample. Yet for the investment to GDP ratio, the effect of the wage share has become insignificant throughout the last decades. As in the full sample, the long-run effect of functional distribution on net exports is still insignificant.

In addition to our focus on the more recent data, we augment the basic error correction models with the stock of private credit to GDP (credit), which in many countries has been substantially increasing since the late 1980s. Following the advise of Stockhammer (2017), we assume that the amount of credit in the economy could be the source of an omitted variable bias if it is not controlled for. Panel unit root tests indicate that credit to GDP is an AR(1) variable in all of the observed economies. In the augmented models of Columns (4)-(6), the estimated effects of the wage share on consumption and investment hardly differ from the preceding estimates for the 1991-2015 sub-period. For net exports, however, a negative long-run effect of the wage share emerges, which may have been concealed by the expansion of credit to the private sector.[17] According to the CD test statistics, the presence of cross-section dependence in the residuals is far less likely with the more recent data. Yet in the augmented models of investment and net exports, the null of cross-section independence is still rejected at the 10% significance level.

[16] Experimentation reveals that the choice of the specific year makes little difference.

[17] Whereas the short-run coefficients of credit are always insignificant, the long-run effect of credit in the investment equation is negative and significant at the 5% level. The latter may initially appear counterintuitive, however a small negative long-run effect of the credit stock might be plausible because of overborrowing.

Table 2.6: ECM models, DCCE estimations, subsample 1991-2015

Dep. var.	(1) $\Delta(C/Y)$	(2) $\Delta(I/Y)$	(3) $\Delta(NX/Y)$	(4) $\Delta(C/Y)$	(5) $\Delta(I/Y)$	(6) $\Delta(NX/Y)$
EC coefficient						
$(\mathrm{C/Y})_{i,t-1}$	-0.420***			-0.716***		
	(0.0994)			(0.107)		
$(\mathrm{I/Y})_{i,t-1}$		-0.608***			-0.857***	
		(0.0594)			(0.131)	
$(\mathrm{NX/Y})_{i,t-1}$			-0.463***			-0.741***
			(0.0903)			(0.0828)
Short-run avg. coef.						
Δ WS	0.290***	0.0185	-0.320***	0.267***	-0.0529	-0.240
	(0.0515)	(0.0532)	(0.0742)	(0.0921)	(0.0434)	(0.162)
Δ credit				0.00697	0.00668	-0.00577
				(0.0111)	(0.0149)	(0.0307)
Long-run avg. coef.						
WS	0.536**	-0.138	-0.345	0.443***	-0.171	-.515**
	(0.214)	(0.114)	(0.258)	(0.124)	(0.137)	(0.222)
credit				0.0129	-0.0447**	0.0617*
				(0.0283)	(0.0184)	(0.0358)
RMSE	0.389	0.469	0.631	0.232	0.186	0.307
CD-stat	-0.06	0.25	-1.28	-0.56	-1.85	-1.88
CD p-val	0.952	0.806	0.202	0.576	0.064	0.060
Observations	439	439	439	439	439	439
No. of groups	20	20	20	20	20	20

Notes: Table reports (DCCE) dynamic common correlated effects mean group estimations for the subsample 1991-2015. Models include cross-section averages of two additional lags. We report the outlier-robust means (Hamilton, 1992) of the regression coefficients for the heterogeneous parameter models. Standard errors are given in parentheses. RMSE is the root mean squared error. CD reports Pesaran (2004) CD test statistics and p-values for the null of cross-section independence. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

2.6 Conclusion

We first estimate the direct link between functional income distribution and economic growth in a panel of 23 OECD countries by applying a first-difference estimator. The results of this exercise contrast with the conclusions of most post-Keynesian studies, yielding a negative contemporaneous correlation that could be naively interpreted as evidence for a profit-led demand regime. However, due to the endogeneity of the wage share in the business cycle, a causal interpretation for such a regression would be inaccurate. Thus, we test for Granger causality, finding that a rising wage share predicts higher growth rates in the following year, but also that higher growth predicts a rising wage share. Based on these short run correlations, our findings provide tentative support for a wage-led growth regime. However, in addition to the general limitations of Granger causality tests, the positive effect of the wage share on growth is not very robust when heterogeneous parameter models are applied. At the very least, the finding of a significant reverse causality warns against the assumption of a unidirectional causation in the empirical literature on wage- versus profit-led growth.

Nevertheless, our results do support the predictions of the Bhaduri and Marglin (1990) model with regard to the relationship between the functional distribution of income and the composition of aggregate demand. By applying current panel time-series estimators, we distinguish structural relationships from possibly spurious business cycle variations. We find that in the long run a shift of income from labor to capital is associated with a lower consumption to GDP ratio, which is in line with the saving differential suggested by Kenynes and Kalecki. However, in accordance with a neoclassical mechanism, we also find that a decreasing wage share was generally related to higher business investment.

Restricting our focus to more recent decades and controlling for the credit expansion of the 1990s and 2000s, a strong link between wages and consumption persists. Yet, instead of promoting investment, an increase in profits at the expense of labor seems to have driven up net exports in most of the affected economies.

In summary, this chapter confirms the findings of earlier empirical studies (e.g. Stockhammer and Wildauer, 2015), by employing a large panel of countries and a novel empirical approach that emphasizes long-run effects. It concludes that variations in the wage share are related to substantial shifts in the composition of aggregate demand. A lack of private consumption resulting from a decreasing wage share in many economies was initially compensated for via an increase in business investments. Later, net exports appear to have filled this gap; but from a global perspective, reliance on external demand is not a viable strategy. Assuming causal effects of income distribution, Onaran and Obst (2016) have already shown that in a group of integrated economies, a simultaneous decline in the wage share may lead to an overall decline in GDP.

While we have focused on identifying economic regularities, we have also found evidence for a substantial heterogeneity across countries which might be due to different distributions of labor income. In countries where labor income is concentrated in richer households with a high saving rate, the case for wage-led demand is certainly weaker than in countries where wages are equally distributed (see, Palley, 2014 and Skott, 2016). It is thus important that future research focusing on the differences in the effects of functional income distribution takes the interpersonal distribution of wages and profits into account.

2.7 Appendix to chapter 2

Table 2.7: Maddala and Wu (1999) Panel Unit Root test

Specification without trend				Specification with trend	
Variable	lags	chi_sq	p-value	chi_sq	p-value
C/Y	0	52.576	0.234	71.565	0.009
C/Y	1	60.404	0.075	78.756	0.002
C/Y	2	65.939	0.028	77.308	0.003
C/Y	3	54.624	0.180	72.581	0.007
C/Y	4	49.122	0.349	61.103	0.067
I/Y	0	78.700	0.002	57.817	0.113
I/Y	1	132.549	0.000	127.016	0.000
I/Y	2	103.015	0.000	104.347	0.000
I/Y	3	79.849	0.001	72.745	0.007
I/Y	4	87.093	0.000	76.860	0.003
NX/Y	0	75.214	0.004	83.861	0.001
NX/Y	1	80.023	0.001	88.163	0.000
NX/Y	2	64.357	0.038	73.610	0.006
NX/Y	3	61.084	0.067	80.398	0.001
NX/Y	4	43.647	0.571	65.926	0.028
WS	0	53.381	0.212	50.774	0.291
WS	1	64.380	0.038	89.293	0.000
WS	2	48.230	0.383	63.314	0.046
WS	3	52.257	0.244	59.189	0.092
WS	4	49.013	0.353	56.493	0.138
credit	0	33.830	0.908	34.496	0.894
credit	1	28.736	0.978	37.399	0.813
credit	2	23.704	0.997	30.520	0.962
credit	3	25.122	0.995	37.559	0.808
credit	4	28.590	0.979	37.675	0.804

Notes: The null hypothesis is that all series are nonstationary.

Table 2.8: Pesaran (2007) Panel Unit Root test

Specification without trend				Specification with trend	
Variable	lags	Zt-bar	p-value	Zt-bar	p-value
C/Y	0	-1.677	0.047	0.434	0.668
C/Y	1	-2.500	0.006	-0.538	0.295
C/Y	2	-1.876	0.030	0.147	0.559
C/Y	3	-1.452	0.073	0.580	0.719
C/Y	4	0.161	0.564	2.613	0.996
I/Y	0	-1.625	0.052	0.037	0.515
I/Y	1	-3.212	0.001	-2.095	0.018
I/Y	2	-1.821	0.034	-1.298	0.097
I/Y	3	-1.376	0.084	-0.835	0.202
I/Y	4	-0.784	0.216	0.246	0.597
NX/Y	0	-2.063	0.020	-0.314	0.377
NX/Y	1	-1.413	0.079	0.427	0.665
NX/Y	2	-1.017	0.155	1.114	0.867
NX/Y	3	-0.217	0.414	1.401	0.919
NX/Y	4	0.653	0.743	2.315	0.990
WS	0	-2.710	0.003	-0.360	0.359
WS	1	-4.008	0.000	-2.814	0.002
WS	2	-2.580	0.005	-1.220	0.111
WS	3	-1.162	0.123	0.035	0.514
WS	4	0.417	0.661	1.456	0.927
credit	0	0.529	0.702	-0.216	0.415
credit	1	1.111	0.867	2.557	0.995
credit	2	1.981	0.976	3.372	1.000
credit	3	1.645	0.950	3.081	0.999
credit	4	1.192	0.883	1.541	0.938

Notes: The null hypothesis is that all series are nonstationary.

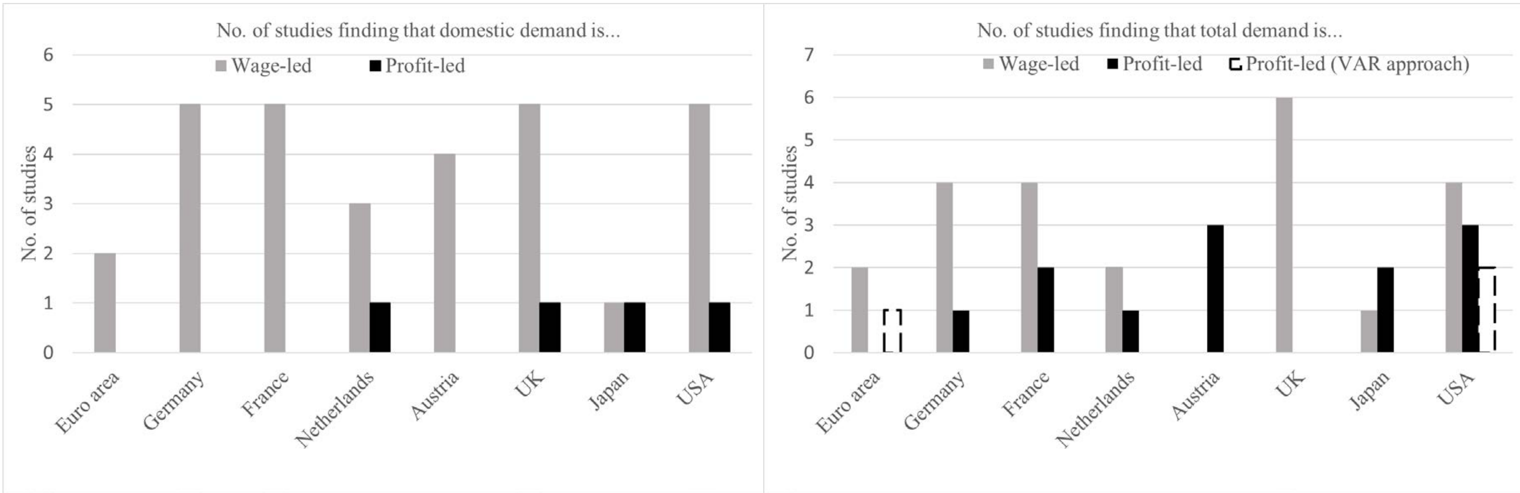


Figure 2.1: Graphical illustration of the literature summary of Stockhammer (2017).

Chapter 3

Income Distribution and Aggregate Saving: A Non-Monotonic Relationship

3.1 Introduction[1]

Is there an empirical link between income distribution and aggregate saving? This chapter suggests *yes*, but in a non-monotonic way. It suggests that at a low level of inequality, more inequality is associated with higher saving, but it also shows that a negative relationship between inequality and saving prevails at high levels of inequality.

Given the secular rise in income inequality, economists increasingly focus on the macroeconomic implications of this development. A link between inequality and saving lies at the heart of this literature: For instance, the debate about secular stagnation has drawn new attention to the Keynesian idea that rising inequality increases the aggregate propensity to save and thus exerts a drag on aggregate demand (e.g., Eggertsson and Mehrotra, 2014; Summers, 2015). Assuming the same positive relationship between inequality and saving, but coming to a different conclusion, the neoclassical growth literature suggests that inequality promotes economic performance by fostering capital accumulation (Bourguignon, 1981). Yet, with regard to global current account imbalances, some studies argue that an increase in inequality lowers private saving and the current account (Ranciere et al., 2012; Al-Hussami and Remesal, 2012; Behringer and van Treeck, 2013).

Although household saving constitutes a common transmission variable in all these strands of literature, the link between income inequality and saving is theoretically and empirically unclear: As richer households tend to have a higher propensity to save than households at the lower end of the income distribution (e.g., Dynan et al., 2004), an increase in income inequality may cause a rise in aggregate saving (Keynes, 1936, 1939). Yet, if households engage in upward-looking interpersonal comparison, middle- and low income earners might lower their saving rate in response to rising top incomes (Drechsel-Grau and Schmid, 2014; Bertrand and Morse, 2016). Thus an increase in inequality could just as well trigger expenditure cascades and a decline in aggregate saving (Alvarez-Cuadrado and El-Attar Vilalta, 2012; Frank et al., 2014).

In line with the theoretical ambiguity, cross-country and panel-data studies that investigate the effect of inequality on national or private saving rates often remain inconclusive (Schmidt-Hebbel and Serven, 2000; Li and Zou, 2004; Leigh and Posso, 2009). With

[1]This chapter is based on joint work with Peter Bofinger. An earlier version appeared as Bofinger and Scheuermeyer (2016). The present version has benefited from the comments of three anonymous referees of the Review of Income and Wealth where it is currently under third round review.

regard to household saving some studies find a negative effect of inequality, albeit they rely on samples of rather few countries (Leigh and Posso, 2009; Alvarez-Cuadrado and El-Attar Vilalta, 2012; Behringer and van Treeck, 2013). The present study is the first that primarily focuses on household sector saving rates, which we prefer over national or private saving rates due to a more direct connection to the theories of interest. By combining saving rates from OECD databases with net income Gini coefficients from the Luxembourg Income Study, this chapter rests on a panel of highly consistent data. Moreover, the Standardized World Income Inequality Database was used to generate a large alternative sample with 792 observations from 29 advanced economies.

In consistence with the theoretical ambiguity and the inconclusiveness of the empirical literature, we do not find a clear linear correlation between inequality and saving. However, we reveal a highly significant hump-shaped relation between inequality and saving that is robust to a large set of controls, including equity and house prices, credit availability, and financial liberalization. We find that the impact of inequality on saving is positive at low levels of inequality, whereas it becomes negative after some turning point, which is located at a Gini between 28 and 32. This hump-shaped pattern is robust to different data sources, estimation techniques, measures of inequality, and sample compositions. Yet the pattern appears to vanish in the aftermath of the financial crisis.

As the availability of credit financing might be a precondition for expenditure cascades (see, e.g. Rajan, 2010, Frank et al., 2014, Bertrand and Morse, 2016), we also test whether the impact of inequality interacts with credit availability and financial market liberalization. We find that rising inequality tends to reduce saving if financial markets are widely liberalized or the ratio of credit to GDP is high. Nonetheless, in both a low-credit and high-credit environment, the hump-shaped relationship between inequality and saving prevails. While we primarily focus on household saving rates, we find some evidence that the hump-shaped effect of inequality also appears for private saving rates, national saving rates, and the current account balance.

The chapter proceeds as follows: Section 3.2 describes the theoretical background to the analysis. Section 3.3 briefly reviews the recent empirical literature on the household, state, and cross-country level. Section 3.4 describes the data, focusing on measures of saving and income distribution. Section 3.5 reports our baseline regression results, followed by an extensive sensitivity analysis, an exploration of interaction effects, and regressions for alternative dependent variables. Section 3.6 discusses the results and concludes.

3.2 Theoretical link between income distribution and household saving

The link between income distribution and aggregate household saving is ambiguous, as there are various opposing effects on the microeconomic level, which might be offsetting in the macroeconomic aggregate: First of all, according to Keynes (1939), the individual propensity to consume decreases with personal income, which implies *"[...] that the collective propensity for a community as a whole may depend (inter alia) on the distribution of incomes within it."* Possible explanations for higher saving rates of richer households are bequests or wealth that enter the utility function as luxury goods (e.g., Carroll, 1998). Moreover, asset-based means testing for social security benefits (e.g., Hubbard et al., 1995; Gruber and Yelowitz, 1999) and a subsistence consumption level that lies above the income of poorer households (Musgrove, 1980) can lower the saving rates of poorer households.

Assuming that the relationship between individual incomes and saving rates is positive, a rising concentration of income at the top should lead to a rise in the aggregate saving rate. However, if consumption or saving decisions of different households are mutually interrelated, the opposite can be true: According to the relative income hypothesis "[...], the frequency and strength of impulses to increase expenditure for one individual depend entirely on the ratio of his expenditures to the expenditures of those with whom he associates." (Duesenberry, 1949, p. 32). Building upon such consumption externalities, Frank et al. (2014) propose a formal model of "expenditure cascades". Similarly, Alvarez-Cuadrado and El-Attar Vilalta (2012) incorporate relative income considerations into an OLG model. In both models, increasing consumption of a reference group encourages additional consumption by households further down the income ranking. On aggregate, a mean preserving spread in incomes thus leads to a decrease in the saving rate.[2]

[2] A decline in the aggregate saving rate can also result from a decline or stagnation of income at the bottom of the distribution. According to the habit persistence theory (Brown, 1952), people lower their saving rate to hold on to their usual consumption level when real income deteriorates. If people are used to steady improvements in living standards, habit persistence may thus implicate lower saving when income growth slows down for certain income groups. Similarly, a decrease in aggregate saving can result when more and more households are falling below a subsistence consumption level. The latter

In conclusion, the prerequisite for a decline in the aggregate saving rate due to rising inequality is that saving rates of low and middle income earners decline sufficiently; so that the increase in the volume of saving, resulting from the shift in income toward households with a larger propensity to save, is overcompensated. To enable this decline in saving, the initial saving rates (or the financial wealth) of low and middle income households have to be sufficiently large. Otherwise, if saving rates (and wealth) are already low, poorer households have to borrow to finance their excess consumption.

3.3 A brief survey of the empirical literature

The link between income distribution and household saving has been tested in a couple of micro- and macro-data studies. Using survey data from the U.S., a highly cited study by Dynan et al. (2004) finds a strong positive correlation between saving rates and household incomes. Yet, based on Canadian data, Alan et al. (2015) indicate that saving rates do not differ substantially across long-run income groups. Like Dynan et al. (2004), Alvarez-Cuadrado and El-Attar Vilalta (2012) find that saving rates increase in permanent income. Moreover, the latter study emphasizes a negative correlation between the income growth of local reference groups (or an increase in inequality) and the saving rates of poorer households. Similarly, Bertrand and Morse (2016) support the relative income hypothesis and "trickle-down consumption" by showing that middle income households consume a larger share of their income when exposed to higher upper income and consumption levels. Based on this result they estimate that in 2005 the aggregate personal saving rate in the US might have been 1.1 to 1.3 percent higher, if income growth at the top had not outpaced growth at median levels. Finally, Drechsel-Grau and Schmid (2014) show that "keeping up with the Joneses behaviour" is not limited to one side of the Atlantic. Using data from the German Socio-Economic Panel they find that an increase in reference consumption by 1% leads households to raise their own consumption by about 0.3%.

Altogether, micro-data evidence supports both the Keynesian- and the relative income hypothesis. Yet it says little about aggregate saving because it cannot tell which of the opposing effects prevails. Therefore we have to refer to macro-data studies, which regress aggregate saving rates on aggregate measures of income distribution.

would be most pronounced, if the subsistence level is a socially acceptable consumption standard that is high enough to affect a large number of households.

In general, cross-country studies on inequality and saving often remain inconclusive and the results vary with the estimation technique and sample composition. Because of data restrictions either national- or private saving rates serve as the (main) dependent variable in most macro-data studies. To provide a better comparability within the literature and to the present study, we restrain our survey to panel regressions and subsamples of data from developed economies or OECD members. Drawing on this selection, Schmidt-Hebbel and Serven (2000), Li and Zou (2004), as well as Leigh and Posso (2009) do not find a consistent relationship between inequality and saving. Smith (2001), however, reports a positive effect of inequality on private saving.

To our knowledge, there are only three studies that (also) examine the effect of income distribution on the saving rate of the household sector. Regressing household saving on lagged top income shares, in a panel of 10 developed economies observed between 1975 and 2002, Leigh and Posso (2009) find no significant effect of inequality. In contrast, Alvarez-Cuadrado and El-Attar Vilalta (2012) suggest a negative impact of inequality on aggregate saving. Drawing on a sample of 6 developed economies, observed between 1954 and 2007, they find a negative effect of the top 5% income share, which is highly significant under a range of different econometric specifications. A recent study by Behringer and van Treeck (2013) primarily deals with the effect of income distribution on the current account. Yet it also takes a look at saving rates and financial balances of the household sector. In a sample of G7 economies, the study finds a significant negative effect of the top 5% income share, while the Gini coefficient appears to be insignificant.

Altogether, the literature about the relationship between inequality and saving remains inconclusive, which might be due to some deficiencies: First, there are only few studies that examine the aggregate saving rate of the household sector. Second, the studies which focus on household saving are based on very few countries. Third, the existing literature does not control for a number of covariates, like wealth effects, which could lead to an omitted variable bias; and fourth, it does not account for a non-monotonic relationship.

3.4 Data description

3.4.1 Saving rates and sample composition

Most existing studies focus on national saving, which measures the total amount of saving in the economy, including households, firms and the government. Yet, since most theories about saving and inequality refer to household behavior, we prefer to focus on household saving rates, while we will glance at broader measures of saving and the current account balance at the end of this chapter.

Although household saving rates are less readily available than national saving rates, we are able to compose a fairly large sample by combining data from the OECD National Accounts Database with data from the OECD Economic Outlook. To benefit from a homogenous sample of high quality data, we limit our panel to high-income OECD countries, as defined by the World Bank classification. The OECD calculates saving by subtracting household consumption expenditures from household disposable income, net of fixed-capital depreciation. Capital holding gains are not included, which is conducive to our focus on active saving behavior. Dividing the saving volume by the disposable income of the household sector yields the saving rate.[3]

3.4.2 Inequality data

The use of the right inequality dataset for cross-national research is controversial (see, Atkinson and Brandolini, 2001, Jenkins, 2015, and Solt, 2015). So far, the trade-off between a larger size of the dataset and a greater comparability among observations has not been entirely resolved. Hence, we deploy two different datasets in order to ensure the robustness of our baseline results. To provide the best comparability, we use the Key Figures from the Luxembourg Income Study (LIS), which are calculated from harmonized microdata. In addition, we also deploy the Standardized World Income Inequality Database (SWIID), which is a secondary-source dataset that maximizes the coverage of countries and years. In any case our primary measure of inequality is the Gini of household income after taxes and transfers.

[3]Notably, the household sector includes unincorporated enterprises and in most cases also non-profit institutions serving households.

The LIS Key Figures are widely regarded as the most consistent inequality measures (see, Solt, 2015 and Ravallion, 2015). Yet their coverage is very limited, restricting our regression sample to only 143 observations from 25 countries. While the selection of countries is in line with our focus on advanced economies, the time dimension is very short and obstructive to many robustness tests, e.g. for differing sample compositions and alternative estimators.

Thus we also deploy version 5.0 of the Standardized World Income Inequality Database Solt (2009, 2016) as an alternative. The SWIID aims to provide the most comparable data for the broadest possible sample of countries and years by collecting Ginis from a large number of sources like cross-national inequality databases, national statistical offices, and scholarly articles. Market and net Ginis from the LIS are added as a benchmark of most reliable data. As the source data is often not consistent due to different income definitions or accounting units, the SWIID uses a multiple-imputation algorithm to estimate standardized net and market Ginis for all country-years that are not yet covered in the LIS. To reflect the uncertainty associated with these estimates, the SWIID reports 100 imputations for each observation, generated via Monte Carlo simulations.

There are two alternative paths to employ the SWIID data in regression analysis. The first is to average the imputations and to use the resulting point estimates with usual regression techniques, thereby simply ignoring the uncertainty in the inequality data. The second, which is recommended by the author of the SWIID, is to deploy multiple imputation tools that explicitly account for data uncertainty within the estimation results. As the uncertainty related to Ginis from high-income OECD countries is relatively low, this chapter primarily uses point estimates of the SWIID data. However, we also employ multiple imputation estimation techniques to test for the robustness of our results.

A recent paper by Jenkins (2015) criticizes the comparability and quality of the data in the SWIID. However, Solt (2015) shows that most of this criticism does not apply to the current version of the database. In general, the construction and use of secondary datasets comes with some pitfalls, which are described in a seminal paper by Atkinson and Brandolini (2001). Yet Solt (2015, 2016) convincingly shows that the SWIID incorporates the advise from Atkinson and Brandolini (2001, 2009) and thus poses the best choice among inequality datasets that cover many countries and years.

3.4.3 Control variables

To isolate the true impact of income distribution on saving, we control for a number of variables that are so far neglected in the literature on inequality and saving. First of all, we are concerned about wealth effects being a cause of spurious regressions. Rising asset prices may cause a drop in saving, as people feel wealthier and are able borrow against higher collateral (e.g. Slacalek, 2009; Hüfner and Koske, 2010). However, if an asset bubble is associated with growing income inequality, these wealth effects may misleadingly be attributed to income distribution. To avoid such an omitted variable bias, we employ an indicator of real house price developments (*houses*) and real stock market returns (*equities*).

Another potentially important control is the availability of credit, which we proxy with the ratio of private credit to GDP (*credit*). Whereas financial liberalization may enhance saving opportunities, a greater availability of credit could as well boost private consumption by relaxing borrowing constraints (e.g., Bandiera et al., 2000). As an expanding financial sector may affect income distribution (e.g., Delis et al., 2014; Bumann and Lensink, 2016), omitting financial depth may cause a bias in the estimated effect of inequality.

The remaining control variables are common in the literature on inequality and saving. The old-age dependency ratio (*depend*) is defined as the share of population aged 65 or older over the working-age population. According to the life-cycle hypothesis (Modigliani, 1970) we expect a negative sign for its estimated coefficient. The variable *incgrow* denotes the growth rate of households' real disposable income per capita.[4] Because of habit persistence an increase in income may lead to an increase in saving. However, if households are forward looking, consumption may also rise in anticipation of rising future incomes. Real interest rates are measured by the real return on long term government bonds (*interest*). Although in standard macroeconomic models a higher interest rate increases the attractiveness of saving compared to consumption, the sign of its effect is ambiguous. If households pursue a fix amount of savings, higher interest rates could as well reduce saving because less money must be put aside to reach a saving target. Further controls are the fiscal balance (*fiscal*), to account for Ricardian equivalence; the natural logarithm

[4]We prefer the growth rate of household disposable income over the GDP growth rate, due to less severe concerns about reverse causality and its more direct impact on the household sector.

of GDP per capita (*ln(gdppc)*); and the inflation rate (*infl*). A more detailed description of the sources and derivations of our variables can be found in the Appendix. Table 3.1 contains summary statistics.

Finally, the saving rate of private households is likely to be affected by factors that are unobservable or difficult to measure. For instance, cultural attitudes (like the proneness for competitive thinking) could be a source of omitted variable bias, if they affect attitudes towards consumption as well as the political stance towards redistribution.[5] To control for such time invariant factors our baseline model includes country fixed effects.

Table 3.1: Summary statistics

Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**N**
saving$_{hh}$	7.930	5.989	-9.043	25.776	792
gini$_{LIS}$	28.328	4.123	19.7	37.1	142
gini$_{SWIID}$	28.282	4.403	17.964	48.74	792
atk	0.142	0.04	0.073	0.235	142
S80/S20	5.167	1.684	3.057	13.414	151
P90/P10	3.668	0.794	2.43	5.732	142
P90/P50	1.825	0.176	1.505	2.231	142
top1inc	8.01	2.679	3.97	18.33	427
depend	20.888	4.732	6.433	36.018	792
incgrow	2.391	2.958	-11.046	15.995	792
interest	3.045	2.935	-14.992	20.998	792
fiscal	-2.397	4.593	-32.554	18.696	792
ln(gdppc)	10.303	0.329	8.762	11.346	766
infl	3.986	3.602	-4.48	24.54	792
equities	4.337	23.498	-47.79	105.33	749
houses	1.656	7.092	-17.241	38.831	685
credit	89.863	44.031	20.84	227.753	757
finreform	75.086	23.418	9.524	100	527
saving$_{prvt}$	7.875	4.047	-4.215	23.285	527
saving$_{net}$	7.996	5.783	-12.653	31.164	713
saving$_{gross}$	24.272	5.408	6.118	41.745	723
current account	-0.145	4.639	-14.575	16.232	766

[5] Catte and Boissinot (2005) emphasize further factors, which could explain differences in household saving rates. These include the number of unincorporated enterprises in the household sector, the provision of public goods, the role of direct versus indirect taxation, and the design of the pension system. However, after adjusting the data for differences in public provision and the tax system, Catte and Boissinot (2005) find only modest effects on the level and international differences in saving rates.

3.5 Empirical findings

We now turn to the empirical assessment of the relationship between inequality and household saving. First, we present our regression model along with our baseline results. Next, we show that the results are robust to data uncertainty, endogeneity, alternative inequality measures, different sample compositions, and a flexible functional form. Then, we test whether the relationship between inequality and saving interacts with financial market conditions. Finally, we analyze the effect of inequality on some broader measures of saving as well as the current account balance.

3.5.1 Baseline results: A hump-shaped relationship

The two following tables present the results of our baseline regressions, using either the LIS or the SWIID dataset. The baseline estimation equation is:

$$\text{saving}_{it} = \alpha + \beta_1 \text{gini}_{it} + \beta_2 \text{gini}_{it}^2 + \beta' \text{X}_{it} + \alpha_i + (\lambda_t) + \epsilon_{it}, \tag{3.1}$$

where $saving_{it}$ is the aggregate saving rate of the household sector in country i and year t.[6] Among the regressors we focus on the Gini of net incomes, which we include in a linear and a squared form, to allow for a non-linear relationship. The vector X_{it} denotes our set of control variables; α_i are country fixed effects; and ϵ_{it} stands for the error terms. The standard errors are adjusted for the presence of arbitrary heteroskedasticity and autocorrelation.[7] Time fixed effects λ_t are introduced whenever the degrees of freedom would not become too small. Using inequality data from the LIS limits our regression sample to a maximum of 143 observations from 25 countries. The panel is highly unbalanced, with the earliest observation being from 1961 and the latest from 2013.

[6] Some previous studies consolidate the annual data into 5-year averages, to deal with gaps in the data and to weaken serial correlation in the residual. Our regression results are very similar with averaged data (available upon request). Yet we prefer the use of annual data as most of the benefits of averaging are obsolete with our dataset and the use of cluster robust standard errors.

[7] We use cluster robust standard errors, which were developed by Wooldridge (2002), Williams (2000), Rogers (1994), and Froot (1989). As this methodology was developed for panels with a reasonably large cross section relative to the time dimension, cluster robust estimates should be reliable for the LIS regression sample. Yet the time dimension is about equal to the cross-sectional dimension in the SWIID regression sample. Thus we also estimated alternative regressions with Driscoll-Kraay standard errors, which are consistent for autocorrelation and cross-sectional dependence, but have been developed for large T asymptotics. Results are very similar and can be provided upon request.

Table 3.2: Baseline regression models using Ginis from the LIS

	(1) POLS	(2) POLS	(3) FE	(4) FE	(5) FE	(6) FE
gini	-0.0109	3.870**	0.0528	3.310**	0.277*	3.473***
	(0.188)	(1.406)	(0.223)	(1.236)	(0.160)	(0.899)
$gini^2$		-0.0675***		-0.0574**		-0.0550***
		(0.0231)		(0.0216)		(0.0153)
depend	-0.0314	0.000483	-0.672**	-0.627**	-0.765**	-0.753**
	(0.163)	(0.168)	(0.240)	(0.225)	(0.354)	(0.316)
incgrow	0.188	0.214	0.339***	0.344***	0.273**	0.288**
	(0.165)	(0.166)	(0.0924)	(0.0835)	(0.119)	(0.108)
interest	0.310	0.380	-0.178	-0.115	-0.366*	-0.279
	(0.328)	(0.343)	(0.118)	(0.124)	(0.199)	(0.205)
fiscal	-0.384***	-0.381***	-0.430***	-0.440***	-0.532***	-0.526***
	(0.114)	(0.117)	(0.0644)	(0.0600)	(0.0798)	(0.0875)
ln(gdppc)					-0.983	-2.009
					(6.508)	(5.004)
infl					0.214	0.225
					(0.290)	(0.232)
equities					-0.00999	-0.00766
					(0.0169)	(0.0148)
houses					0.0380	0.0234
					(0.0422)	(0.0476)
credit					-0.0133	-0.00276
					(0.0200)	(0.0173)
Observations	143	143	143	143	108	108
Countries	25	25	25	25	24	24
R-sq	0.148	0.194	0.428	0.476	0.568	0.610
Turning-Point		28.67		28.83		31.55
CI 90%		[24.90; 30.79]		[25.73; 32.63]		[28.76; 35.97]
Slope: $gini_{min}$		1.17**		1.01***		1.27***
Slope: $gini_{max}$		-1.25***		-1.05**		-.71**
SLM p-val		0.014		0.014		0.024

Notes: Table reports pooled OLS (POLS) and fixed-effects (FE) regressions. Dependent variable is the saving rate of the household sector. Cluster robust standard errors are reported in parentheses. The bottom part of the table reports the turning points of the inequality effect and the results of the Sasabuchi-Lind-Mehlum (SLM) test for a hump-shaped relationship. CI-90% denotes the 90% Fieller confidence intervals for the turning point. To ease comparison slopes at $gini_{min}$ and $gini_{max}$ are uniformly measured at the bounds of the maximum sample of 143 observations, i.e. at Ginis of 20 and 38. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.2 presents the estimation results. Each pair of columns reports two identical models, which only differ by the inclusion of the quadratic term of the Gini in the even numbered columns. Columns (1) and (2) report pooled OLS estimates, whereas Columns (3)-(6) contain results from fixed effects regressions. We exploit the maximum number of available observations by focusing on small models in Columns (1) to (4). To correct for a possible downward bias in the estimated effect of inequality, we add two measures of asset price movements (*equities* and *houses*) and the credit to GDP ratio (*credit*) in Columns (5) and (6). Following preceding studies, we additionally include the log of real income per capita (*ln(gdppc)*) and the inflation rate (*infl*).

In line with earlier studies, Table 3.2 does not show a clear linear relationship between income inequality and household saving. When the standard set of control variables is applied, the effect of inequality is very small and far from significant. Yet, after the inclusion of the additional controls, the estimated effect of inequality becomes positive at the 10% level.

Above all, however, the estimated coefficients of *gini* and $gini^2$ in Columns (2), (4) and (6) indicate a hump-shaped function between inequality and saving, which prevails with both sets of control variables. To asses the statistical significance of the nonlinear relationship, the even numbered columns report the results of the Sasabuchi-Lind-Mehlum (SLM-Test) together with the slopes at the minimum and maximum values of the Gini in our sample.[8] In addition, we report the Fieller 90% confidence intervals for the turning points. The SLM-Tests reject the null of a monotone or U-shaped relationship in favor of an inverted-U-shaped (concave and hump-shaped) relationship in each specification. With the smaller pooled OLS and fixed effects models in Columns (2) and (4), the turning points are estimated at Ginis of 28.7 and 28.8, respectively. Thus the point, at which the marginal effect of inequality becomes negative, corresponds roughly to the median value of the Gini in our regression sample. In the extended model of Column (6) the estimated turning point shifts towards a Gini of 31.6, indicating that the new controls may have resolved a small downward bias.[9]

[8]The SLM-Test was developed by Lind and Mehlum (2010), based on the work of Sasabuchi (1980). To allow for comparability between different models, we report the slopes at the boundaries of the sample from Column (1), i.e. at Ginis of 20 and 38.

[9]In parts, the shift to the right is also caused by changes in the sample composition: When we run regression (4) on the reduced sample of 108 observations from regression (6), the turning point is estimated at a Gini of 30

Table 3.3: Baseline regression models using Ginis from the SWIID

	(1) POLS	(2) POLS	(3) FE	(4) FE	(5) FE	(6) FE	(7) FE	(8) FE
gini	-0.117	1.427	-0.0373	2.386***	0.138	3.218***	0.0513	3.159***
	(0.168)	(1.079)	(0.195)	(0.659)	(0.204)	(0.635)	(0.160)	(0.711)
$gini^2$		-0.0263		-0.0426***		-0.0533***		-0.0537***
		(0.0182)		(0.0130)		(0.0107)		(0.0119)
depend	-0.325**	-0.309**	-0.671***	-0.677***	-0.676***	-0.715***	-0.849***	-0.882***
	(0.143)	(0.140)	(0.118)	(0.128)	(0.188)	(0.156)	(0.203)	(0.152)
incgrow	0.448***	0.468***	0.271***	0.274***	0.385***	0.382***	0.426***	0.417***
	(0.101)	(0.107)	(0.0582)	(0.0611)	(0.0680)	(0.0642)	(0.0583)	(0.0494)
interest	-0.192	-0.175	-0.100	-0.0965	-0.130	-0.103	0.0306	-0.0215
	(0.158)	(0.157)	(0.108)	(0.112)	(0.176)	(0.156)	(0.191)	(0.159)
fiscal	-0.475***	-0.463***	-0.416***	-0.436***	-0.422***	-0.433***	-0.349**	-0.363***
	(0.155)	(0.155)	(0.103)	(0.0964)	(0.111)	(0.0959)	(0.127)	(0.111)
ln(gdppc)					-0.346	-1.114	-5.421	-7.502
					(4.933)	(4.035)	(8.714)	(7.654)
infl					0.0588	0.0887	0.196	0.201
					(0.162)	(0.104)	(0.220)	(0.168)
equities					-0.0155**	-0.0134**	-0.0151	-0.0163
					(0.00663)	(0.00513)	(0.0118)	(0.00994)
houses					-0.0758***	-0.0714**	-0.0539**	-0.0450*
					(0.0262)	(0.0271)	(0.0226)	(0.0236)
credit					-0.0249	-0.0152	-0.0370	-0.0252
					(0.0215)	(0.0181)	(0.0232)	(0.0202)
year-dummies	No	No	No	No	No	No	Yes	Yes
Observations	792	792	792	792	616	616	616	616
Countries	29	29	29	29	27	27	27	27
R-sq	0.223	0.239	0.433	0.458	0.549	0.583	0.573	0.608
Turning-Point		27.09		27.97		30.20		29.40
CI 90%				[25.04; 33.23]		[26.91; 34.02]		[26.59; 32.32]
Slope: $gini_{min}$		0.48		0.85***		1.30***		1.23***
Slope: $gini_{max}$		-1.15*		-1.79***		-2.00***		-2.11***
SLM p-val		0.14		0.005		0.0002		0.0003

Notes: Table reports pooled OLS (POLS) and fixed-effects (FE) regressions. Dependent variable is the saving rate of the household sector. Cluster robust standard errors are reported in parentheses. The bottom part of the table reports the turning points of the inequality effect and the results of the Sasabuchi-Lind-Mehlum (SLM) test for a hump-shaped relationship. CI-90% denotes the 90% Fieller confidence intervals for the turning point. To ease comparison slopes at $gini_{min}$ and $gini_{max}$ are uniformly measured at the bounds of the maximum sample of 792 observations, i.e. at Ginis of 18 and 49. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Using inequality data from the SWIID vastly expands the regression sample. Yet Table 3.3, which is based on a sample of up to 792 observations from 29 countries, presents very similar results with respect to the hump-shaped relationship between inequality and saving. Whereas a linear effect of inequality is never significant with the SWIID sample, the coefficients of *gini* and $gini^2$ are again highly significant in all fixed effects estimations.

The positions of the turning points are similar to the estimates from the LIS sample as well. In the small fixed effects model of Column (4), the marginal effect of inequality turns from positive to negative at a Gini of 28. After introducing the additional controls in Columns (5) and (6), the turning point shifts slightly rightwards to a Gini of 30.2. In contrast to the LIS sample, asset prices are now negatively correlated with the saving rate. In Columns (7) and (8) we finally add year-dummies to account for common shocks like the global financial crisis. While only few of these dummies are significant, their introduction slightly affects the estimates of the other control variables. Nonetheless, for *gini* and $gini^2$ the results remain almost unchanged, yielding a hump-shaped relationship with a turning point at a Gini of 29.4.[10] In sum, our regression models resemble earlier studies that do not find a linear relationship between income inequality and the aggregate saving rate. However, by introducing a quadratic term, we reveal a hump-shaped relationship, which peaks at a net Gini roughly between 28 and 32.

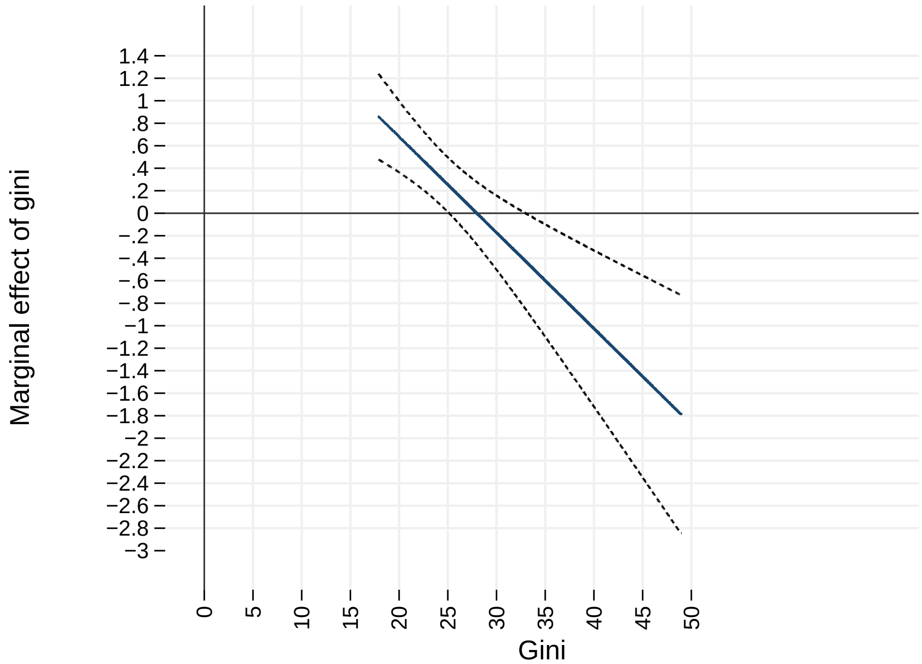


Figure 3.1: Marginal effect of inequality on saving at different levels of inequality
Notes: Values are calculated from the results of Table 3.3, Column (4). The downwards sloping line plots the marginal effect of inequality. Surrounding dotted lines represent the 90% confidence intervals.

[10]Following Grigoli et al. (2014) and Loayza et al. (2000) we also added the share of urban population, terms of trade, and the young age dependency ratio as additional regressors. Whereas the latter two variables are positively related to saving, the results for *gini* and $gini^2$ are almost unchanged by this exercise. Finally, the concave relationship is also robust to the fixed effects model from Schmidt-Hebbel and Serven (2000), who control for young- and old-age dependency, gdp growth, per capita GDP and also the square of per capita GDP. Results are available upon request.

Figure 3.1 illustrates the marginal effect of inequality on saving across different values of the Gini. It pictures how the effect of inequality is decreasing with an increasing level of inequality. The marginal effect of inequality ranges from 0.85 at the smallest Gini in the sample (Gini of 18, observed in Sweden 1990) toward -1.79 at the upper bound (Gini of 49, in Chile 2009). In line with the results from the SLM-test, the confidence intervals reveal a significantly positive effect of inequality for Ginis ranging from 18 to 25 and a significantly negative effect for Ginis above 33. To get an idea of the countries that have driven the non-linear effect, Figure 3.2 plots the Ginis observed in 1995 along with the associated marginal effects.[11] Looking at the two polar cases, the figure predicts a strong positive effect of rising inequality on saving in Sweden and a negative effect in the United States.

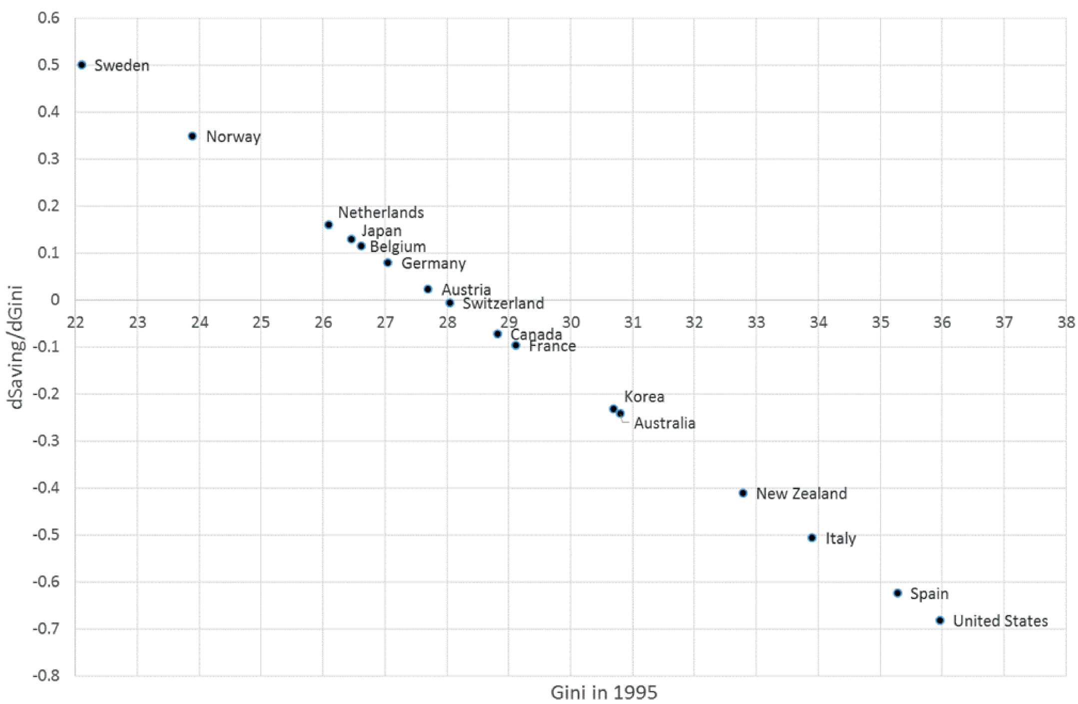


Figure 3.2: Marginal effect of inequality on saving at 1995 inequality levels
Notes: Values are calculated from the results of Table 3.3, Column (4).

[11] Corresponding figures for different time periods are available upon request. We report the marginal effects in 1995 as it constitutes a time period that stands rather at the beginning of the sample, but already contains most of the countries.

3.5.2 Robustness Tests

This section analyzes the robustness of the hump-shaped relationship. As many of the following robustness tests require a comprehensive sample, we always apply inequality data from the SWIID, if not mentioned otherwise.

Multiple imputation estimations

First, we test whether the uncertainty that is associated with the SWIID data affects our results. Therefore, we follow the advise from Solt (2016) and employ a multiple imputation technique to account for data uncertainty. Essentially, Stata's multiple imputation estimation routine, which we apply in this section, runs repeated regressions for each of the 100 imputations of the net Gini and then pools the resulting estimates following the combination rules proposed by Rubin (1987). Thus the estimated coefficients and standard errors are adjusted for the variability between imputations, whereas regressions on averaged data treat the Gini from the SWIID as an error-free variable.[12]

Table 3.4 presents the multiple imputation regressions. To provide direct comparability, each regression exactly resembles the quadratic models of the baseline specification, but is estimated with the multiple imputation technique. Just like in the baseline table we find a hump-shaped relationship between inequality and saving. The effect of inequality remains highly significant and the locations of the turning points almost unchanged, although the estimated coefficients become somewhat smaller and the standard errors slightly larger.[13] Altogether, the enhanced statistical accuracy stemming from multiple imputation estimations hardly affects our results, which means that we can safely proceed with less computational intensive regression techniques.

[12] Brownstone and Valletta (2001) offer an excellent summary of the multiple estimation technique and its applications in economics.

[13] The resulting slightly decreased standard errors together with flattened regression lines are surprising, given that we would normally expect that multiple imputation estimations increase the standard errors. We are grateful to Frederic Solt for pointing out a possible explanation: In cases where influential outliers with large standard errors are pulling up the coefficients, using multiple imputations may flatten the coefficients and also estimate them with more precision.

Table 3.4: Multiple-imputation estimates

	(1) POLS	(2) FE	(3) FE	(4) FE
gini_{mi}	1.388	2.179***	2.939***	2.917***
	(1.042)	(0.665)	(0.646)	(0.696)
$\text{gini}^2{}_{mi}$	-0.0256	-0.0389***	-0.0487***	-0.0496***
	(0.0176)	(0.0130)	(0.0112)	(0.0119)
depend	-0.310**	-0.683***	-0.712***	-0.883***
	(0.140)	(0.126)	(0.159)	(0.156)
incgrow	0.468***	0.274***	0.384***	0.419***
	(0.108)	(0.0612)	(0.0657)	(0.0504)
interest	-0.176	-0.0975	-0.108	-0.0173
	(0.157)	(0.112)	(0.156)	(0.161)
fiscal	-0.463***	-0.435***	-0.431***	-0.361***
	(0.155)	(0.0972)	(0.0983)	(0.113)
ln(gdppc)			-1.059	-7.421
			(4.105)	(7.754)
infl			0.0829	0.201
			(0.109)	(0.171)
equities			-0.0136**	-0.0161
			(0.00526)	(0.0101)
houses			-0.0726**	-0.0459*
			(0.0279)	(0.0238)
credit			-0.0159	-0.0261
			(0.0183)	(0.0204)
year-dummies	No	No	No	Yes
Observations	792	792	616	616
Countries	29	29	27	27
Turning-Point	27.06	28.07	30.19	29.4

Notes: Table presents multiple-imputation estimates of the baseline pooled OLS (POLS) and fixed effects (FE) regression models. Dependent variable is the saving rate of the household sector. Cluster robust standard errors are reported in parentheses. The final line of the table reports the turning points of the inequality effect. Ginis are sourced from the SWIID.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Addressing endogeneity via lag identification, 2-SLS and System GMM

So far we have merely assumed that we measure a causal effect of inequality on saving. Yet, although the case for reverse causation is not very strong, some simultaneity bias cannot be ruled out. This section applies various instrumental variable techniques to counter the potential endogeneity of inequality.[14]

[14] While the present chapter focuses on the potential endogeneity of the Gini coefficient, it is as well possible that the results are biased due to endogenous control variables. The working paper version of this chapter demonstrates that instrumenting potentially endogenous controls (like income growth, interest rates and the fiscal balance) does not alter the estimated effect of inequality.

Table 3.5: Lagged regressors, 2-SLS, and System-GMM

	(1) Lag t-1 FE	(2) 2SLS FE	(3) 2SLS FE	(4) Sys. GMM	(5) 2SLS FE	(6) 2SLS FE
$saving_{t-1}$			0.816***	0.946***		
			(0.0260)	(0.0344)		
gini	2.190***	3.299***	0.913***	1.032**	13.58***	10.84***
	(0.608)	(0.532)	(0.344)	(0.516)	(2.381)	(3.354)
$gini^2$	-0.0393***	-0.0577***	-0.0160***	-0.0176*	-0.244***	-0.179***
	(0.0120)	(0.0105)	(0.00554)	(0.00955)	(0.0443)	(0.0548)
depend	-0.689***	-0.709***	-0.0374	0.00848	-0.801***	-1.045***
	(0.138)	(0.127)	(0.0338)	(0.0427)	(0.162)	(0.173)
incgrow	0.252***	0.269***	0.404***	0.136	0.329***	0.283***
	(0.0895)	(0.0615)	(0.0380)	(0.0998)	(0.0803)	(0.0683)
interest	-0.136	-0.0987	-0.0566	-0.0442	-0.0849	-0.0162
	(0.122)	(0.121)	(0.0360)	(0.0459)	(0.0865)	(0.0735)
fiscal	-0.326***	-0.453***	-0.194***	-0.00852	-0.459***	-0.492***
	(0.0945)	(0.0937)	(0.0290)	(0.0384)	(0.0666)	(0.0661)
Instruments		L(2/3).gini	L(2/3).gini	L(2/3).	avg.gini(n-i)	$gini_{Sweden}$ x proxSweden
Observations	793	772	769	789	766	710
Countries	29	29	29	29	29	28
AR(1) p-val				0.00003		
AR(2) p-val				0.816		
Hansen J p-val		0.265	0.741	0.086	exact. indent.	exact. indent.
KP LM p-val		0.027	0.031	0.048/0.032	0.0007	0.0005
KP F-Stat		62.991	63.980	1.260/0.716	6.165	5.904
Turning-Point	27.86	28.58	28.52	29.31	27.77	30.29
SLM p-val		0.000	.009	.042	.000	.001

Notes: Dependent variable is the saving rate of the household sector. Column (1) presents a fixed effects model with regressors that are lagged for one period. Columns (2) and (3) report 2SLS (two-stage least squares) fixed effects estimations, where gini and $gini^2$ are instrumented by lags 2 and 3. Column (4) reports a one-step system GMM estimation with cluster robust standard errors, a collapsed instrument matrix, and orthogonal deviations. All variables except depend are treated as endogenous. Columns (5) and (6) present 2SLS estimates with fixed-effects. Standard errors are robust to heteroskedasticity and autocorrelation. In (5) inequality is instrumented through the average of the Ginis of the other countries in the sample, *avg.gini(n-i)*. In (6) the instrument is the product of inequality in Sweden and the cultural proximity of each country with Sweden, $gini_{Sweden}$ *x proxSweden*. With system GMM, AR(1) and AR(2) report the p-values of the Arellano-Bond test for autocorrelation of the residuals. The null of the Hansen J-test (of overidentifying restrictions) is that the instruments are valid. The null of the Kleibergen-Paap (KP) LM test is that the equation is underidentified. The Kleibergen-Paap Wald rk F-statistic can be used to assess the strength of the instruments. The bottom part of the table reports the turning points of the inequality effect and the results of the Sasabuchi-Lind-Mehlum (SLM) test for a hump-shaped relationship. Ginis are sourced from the SWIID. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In Column (1) of Table 3.5 we follow the simplest approach for causal inferences in a panel setting by using lagged instead of contemporaneous values of the explanatory variables. The results are almost identical to the results from estimations with contemporaneous regressors, confirming the hump-shaped relationship with a peak value that is roughly located at a Gini of 28. The same is true when we vary the lag length between 2 and 5 years (results are available upon request), similarly to the approach taken by Leigh and Posso (2009).

In Columns (2) and (3) we deal with a possible simultaneity bias by instrumenting *gini* and $gini^2$ through their second and third period lags.[15] Column (3) additionally includes a lagged dependent variable to capture feedback effects, which could be running from past saving towards current inequality. Regardless of the choice of a static or a dynamic specification, our results show a highly significant concave relationship between inequality and saving with a turning-point at a Gini of roughly 28.5. The test statistics show that the instruments are both relevant and orthogonal to the error term. Above all, the Hansen J test does not reject its null of instrument orthogonality (p-value of 0.26 in the static and 0.74 in the dynamic model), whereas the Kleibergen-Paap rk LM statistic rejects the null of underidentification (p-value of 0.03 in both models). The instruments' relevance is also underlined by the Kleibergen-Paap rk Wald F statistics of 63 and 64, suggesting a maximal relative IV bias of less than 5%. Whereas the large and highly significant coefficient of the lagged saving rate indicates a high degree of persistence, the coefficients of the other regressors are considerably smaller than in the static models. However, in dynamic models the coefficients of the saving determinants only capture short-run effects, which can be difficult to measure as a large share of variation is captured by the lagged dependent variable.

When dynamic fixed effects models are applied on short panels, the coefficient of the lagged dependent variable y_{it-1} is correlated with the error term and thus downward biased (see, Nickell, 1981). Although such a dynamic panel bias should be very small due to the long time dimension of our panel, we follow the convention in the literature (e.g. Loayza et al., 2000 and Grigoli et al., 2014) by also reporting system GMM estimates. The system GMM estimator (Blundell and Bond, 1998; Arellano and Bover, 1995) is an advancement of the difference GMM estimator (Arellano and Bond, 1991), which applies a first difference transformation to eliminate the country fixed effects. To circumvent a dynamic panel bias, second and higher lags of the dependent variable (in levels) are used as instruments for $y_{it-1} - y_{it-2}$. The other endogenous regressors ($X_{it} - X_{it-1}$) are also instrumented via their second and higher lags. One weakness of difference GMM is a poor performance in finite samples and with persistent dependent variables. To mitigate this

[15] We use the xtivreg2 stata routine by Baum et al. (2003) and Schaffer (2010) to estimate a 2-SLS model with fixed effects and cluster-robust standard errors.

problem, system GMM adds an additional equation in levels, thus building a system of two simultaneous equations. For the levels equation lagged first differences are used as instruments, assuming that the additional instruments are orthogonal to the fixed effects.

Column (4) presents the result from our system GMM estimation. To mitigate an over-fitting of endogenous variables with too many instruments, we apply a collapsed instrument matrix (see, Roodman, 2009a) and restrict the instruments for the transformed equation to lag 2 and lag 3. We treat *incgrow*, *interest*, *fiscal*, *gini* and $gini^2$ as endogenous, while the dependency ratio is regarded as exogenous. To maximize the sample size in our unbalanced panel, orthogonal deviations are used instead of the first difference transformation. With system GMM the short-run effects of *gini* and $gini^2$ remain significant and the SLM-test indicates a hump-shaped relationship with a turning point at a Gini of roughly 29. Yet, as the instruments are rather weak, the results are less reliable compared to the dynamic 2-SLS estimator.[16]

Altogether, the results from lag identification and 2-SLS confirm the existence of a non-montonic effect of inequality on saving, regardless of whether a static or a dynamic specification is applied. With system GMM the results are quantitatively similar to the dynamic FE model, but associated with a somewhat larger degree of uncertainty. Following Roodman (2009b), we would suggest that the 2-SLS fixed effects estimator is more appropriate than system GMM, because of the relatively large time dimension of our panel.[17] In either case, as our interest lies foremost in the medium to long-run relation between inequality and saving, we prefer the static over the dynamic model specification.

The use of internal instruments is sometimes criticized. Yet external instruments are often not valid (Bazzi and Clemens, 2013) or do not show enough time variation to be applicable as an instrument for income inequality in a panel context. In such a case it is possible to instrument a variable with its value in other countries, assuming that trends in inequality are related across nations, whereas the saving rate in one country is not related

[16] Standard specification tests for system GMM are given at the bottom of the table. Most importantly, the AR(2) p-value confirms the model specification by not rejecting the null of no second order autocorrelation in the error term. However, the Hansen-J-test rejects its null at the 10% level, which may cast doubt on the validity of the instruments. Following Bazzi and Clemens (2013) we also present Kleibergen-Paap LM statistics and Kleibergen-Paap F statistics for the equation using forward orthogonal deviations and for the level equation, respectively. While the KP LM test rejects the null of underidentifications, the KP F statistic is rather low, suggesting that identification might be weak.

[17] Apart from the fact that the large time dimension mitigates the dynamic panel bias with a fixed-effects estimator, a large T potentially results in an overfitting problem due to instrument proliferation with system GMM. While overfitting could be avoided by collapsing the instrument matrix, the latter results in weaker instruments and less reliable estimates.

to the level of inequality in other countries. Along the lines of Checherita-Westphal and Rother (2012), we use the average inequality levels of the other OECD countries as an instrument for income inequality. In addition, we apply the level of inequality in Sweden as an alternative instrument, which has the advantage that its relevance is less affected by the unbalanced structure of our panel.[18] To improve the strength of this instrument, inequality in Sweden was multiplied with each countries cultural proximity to Sweden.[19] Columns (5) and (6) report the results from 2-SLS estimations using these instruments. Both models show a highly significant hump-shaped relationship between inequality and saving and also the turning point is again located at a Gini around 28 or 30. With regard to the relevance of our instruments, the Kleibergen-Paap F statistic suggests a maximal IV bias of less than 15% in both models.

Alternative inequality measures

So far we have measured inequality exclusively via the gini coefficient, which is a very broad measure of income inequality. In this section we test whether a hump-shaped relationship also occurs with alternative measures of income distribution. The results are shown in Table 3.6. In Column (1) we start by applying the Atkinson Index (*atk*) with a weight factor of one. In Column (2) we use the S80/S20 ratio, representing the share of total household income received by the top quintile divided by the income share of the bottom quintile. Columns (3) to (5) present the P90/P10 and the P90/P50 interdecile ratios, which measure the spread between high and low, or high and middle incomes. All the variables where sourced from the LIS Key Figures, apart from the S80/S20 ratio, which comes from the World Bank's WDI database. Next to these survey based measures of inequality, we also use the income share of the richest 1% from the World Top Incomes Database in Columns (6) to (8).

Using the Atkinson Index, which summarizes the entire distribution of income, a hump-shaped relationship between inequality and saving prevails. Moreover, an increasing spread between the income shares (S80/S20) or income levels (P90/P10) of the rich and the poor also stands in a concave relationship with saving. In contrast, the spread between

[18]When a variable is instrumented by its value in other countries, its strength as an instrument is affected by the selection of countries in the panel. We thus limit our panel to the 1970-2013 period for regressions (5) and (6), as our panel is highly unbalanced with only very few countries offering data from the 1960s.

[19]This approach was inspired by Nunn and Qian (2014). Cultural proximity to Sweden is measured by the four cultural dimensions from Hofstede (2001), as proposed in Gründler and Krieger (2016).

the income of the rich and the middle class (P90/P50) is not significantly related to saving, neither in the linear nor in the quadratic model.

Table 3.6: Alternative Data

	(1) FE	(2) FE	(3) FE	(4) FE	(5) FE	(6) FE	(7) FE	(8) FE
atk	195.6**							
	(75.80)							
atk^2	-605.9**							
	(240.1)							
S80/S20		4.419*						
		(2.222)						
$S80/S20^2$		-0.364**						
		(0.158)						
P90/P10			14.56**					
			(6.469)					
$P90/P10^2$			-1.660*					
			(0.817)					
P90/P50				-2.144	57.12			
				(5.943)	(44.86)			
$P90/P50^2$					-15.64			
					(12.36)			
top1inc						-0.355	0.557	-0.125
						(0.343)	(1.328)	(0.419)
$top1inc^2$							-0.0421	
							(0.0502)	
gini								2.572**
								(1.057)
$gini^2$								-0.0470**
								(0.0222)
depend	-0.684***	-0.706**	-0.660***	-0.638**	-0.643**	-0.771***	-0.805***	-0.809***
	(0.221)	(0.303)	(0.219)	(0.249)	(0.249)	(0.131)	(0.143)	(0.101)
incgrow	0.336***	0.228**	0.378***	0.338***	0.354***	0.276***	0.257***	0.217***
	(0.0908)	(0.0919)	(0.0938)	(0.0868)	(0.0821)	(0.0638)	(0.0664)	(0.0674)
interest	-0.134	0.0642	-0.127	-0.173	-0.150	-0.257**	-0.269**	-0.273**
	(0.126)	(0.185)	(0.117)	(0.113)	(0.113)	(0.107)	(0.105)	(0.0985)
fiscal	-0.452***	-0.398***	-0.470***	-0.426***	-0.437***	-0.465***	-0.505***	-0.513***
	(0.0555)	(0.0747)	(0.0666)	(0.0662)	(0.0657)	(0.0990)	(0.0910)	(0.0915)
Observations	143	151	143	143	143	430	430	427
Countries	25	25	25	25	25	18	18	18
R-sq	0.482	0.456	0.465	0.428	0.434	0.602	0.608	0.637
Turning-Point	.16	6.07	4.39		1.83		6.61	27.39
SLM p-val	.0106	.0407	.0296		.13		.407	.0456

Notes: Table reports fixed-effects (FE) regressions. Cluster robust standard errors are in parentheses. Dependent variable is the saving rate of the household sector. The bottom part of the table reports the turning points of the inequality effect and the results of the Sasabuchi-Lind-Mehlum (SLM) test for a hump-shaped relationship.* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

A general problem with inequality data from income surveys is differential non response (see, e.g. Atkinson and Brandolini, 2001), which is why the development of top incomes is possibly not fully reflected in survey-based inequality measures. To address this problem, we deploy top income shares from the World Top Incomes Database (WTID) by Atkinson et al. (2015) as an alternative inequality variable. Being generated by tax collecting agencies, the WTID data could be more reliable than survey data. However, there are also some limitations (see, Atkinson et al., 2011): First, top income shares do not reflect distribution within the middle and lower ranges of the income ranking. Second, the data is based on gross incomes and ignores governmental redistribution. Third, due to diverse tax bases, income definitions, and units of observation the data is not comparable across countries, which is why the data should not be used with estimators that exploit cross-country variations.[20]

With the top income share the relationship between inequality and saving becomes insignificant in the linear (Column 6) and the quadratic (Column 7) model. For the Gini, however, a hump-shaped relationship persists (Column 8), so that we can rule out that the insignificance of the top income share merely results from the altered sample composition.

Altogether, we find that the hump-shaped relationship is robust to several alternative inequality measures. However, neither the P90/P50 decile ratio nor the income share of the richest 1% are significantly related to household saving. According to Frank et al. (2014), expenditure cascades are foremost driven by an increase in inequality at the top of the distribution. Thus, using the P90/P50 ratio or the top1% income share, the insignificance of a concave relationship could be due to a more pronounced decline in the saving rates of the middle class, while the effect is not large enough to result in a significantly negative parameter within a linear model.[21] The negative but insignificant estimates of *P90/P50* and *top1inc* in Columns (4) and (6) could be a hint for such an explanation.

[20] In the full WTIID database there are also some breaks within countries due to changes in tax legislation etc. When compiling our panel we took care to employ homogenous series for all countries, which leads to shorter time dimensions in Finland and the UK (see, Data Appendix).

[21] Van Treeck (2014) suspects differential effects of Ginis and top income shares on financial stability and personal debt-to-income ratios. Behringer and van Treeck (2013) find differential effects on the current account balance.

Different sample compositions

In this section, we test whether the non-monotonic relationship between inequality and saving is robust to variations in the sample composition, in addition to the reduction in sample size that results from the use of the larger regression model. First, we eliminate the top and bottom 5% of the distribution of saving and inequality from the regression sample. As it can be seen in Column (1) of Table 3.7, the hump-shaped relationship is robust to the omission of these outliers and also the turning point is still roughly located at a Gini of around 30.

Next, we strongly limit our sample along the cross-sectional dimension by only including the G7 economies in Column (2). A similar sample has been used in previous studies (see, Alvarez-Cuadrado and El-Attar Vilalta, 2012; Behringer and van Treeck, 2013), which found a negative effect of the top income share. Yet, with our inequality data and the inclusion of the additional control variables, no clear effect of inequality emerges within the G7 sample. Whereas the signs of *gini* and $gini^2$ hint towards a hump-shaped relationship, the effects are far from significant. Possibly this is due to the reduced efficiency, stemming from the very narrow sample. [22]

Moreover, we also check whether the effect of inequality is sensitive to different time periods. When the actual function between inequality and saving is quadratic, the estimated coefficient of inequality is downward biased in a linear regression equation. Yet the bias is small when the regression sample contains only few observations with high values of inequality.[23] As there may have been fewer instances of high inequality, this could explain why Smith (2001) has found a monotonic positive effect within the 1960-1995 period. To test for this supposition, Column (3) reports a regression that only draws on observations from the period 1961-1995.[24] Yet the model yields clear evidence for a hump-shaped relationship, which peaks at a Gini of roughly 28.[25]

In Columns (4)-(6) we continue with restricting the sample along the time dimension. More precisely, we subsequently eliminate the oldest observations, starting with the 1970s in Column (4), the 70s and 80s in (5) and finally also the 90s in (6). In the first two

[22] In regressions that are available upon request, we also tested for the omission of single countries. In all cases a hump-shaped relationship remains significant and the inequality turning-point hardly varies.

[23] In the context of finance and growth, Arcand et al. (2015) offer a detailed description of the bias in linear models when the true relationship is non-monotonic.

[24] We rely on the small regression model in order to utilize the observations from the 1960s because some of the controls from the large model are not available before 1970.

[25] In a standard linear regression equation the effect of inequality is insignificant (Coef. .010; SE. .169).

samples the hump-shaped relationship remains highly significant and the turning-point becomes somewhat larger. Only in the sample that solely draws on the most recent observations no significant effect occurs.

Table 3.7: Restricted country or time samples

	(1) Excluding outliers	(2) G7 countries	(3) 1961-1995	(4) 1980-2013	(5) 1990-2013	(6) 2000-2013
gini	3.300**	1.415	1.809**	4.110***	3.321***	0.530
	(1.404)	(1.149)	(0.821)	(0.851)	(1.062)	(1.314)
$gini^2$	-0.0565**	-0.0242	-0.0324**	-0.0654***	-0.0496**	-0.00379
	(0.0255)	(0.0182)	(0.0148)	(0.0139)	(0.0186)	(0.0248)
depend	-0.829***	-0.691***	-0.235	-0.801***	-0.740***	-0.265
	(0.150)	(0.154)	(0.193)	(0.163)	(0.200)	(0.157)
incgrow	0.275***	0.364**	0.231***	0.361***	0.318***	0.332***
	(0.0468)	(0.105)	(0.0762)	(0.0543)	(0.0495)	(0.0462)
interest	-0.250	0.0203	-0.376***	-0.154	-0.108	-0.0599
	(0.180)	(0.146)	(0.0900)	(0.156)	(0.165)	(0.100)
fiscal	-0.462***	-0.474***	-0.507***	-0.388***	-0.277***	-0.274***
	(0.113)	(0.115)	(0.0847)	(0.0899)	(0.0951)	(0.0567)
ln(gdppc)	5.622*	4.769		-3.878	-7.876	4.857
	(3.186)	(2.757)		(5.320)	(5.655)	(5.426)
infl	0.0581	0.309***		0.0373	-0.0533	-0.431***
	(0.126)	(0.0823)		(0.148)	(0.220)	(0.146)
equities	-0.0116*	-0.0136**		-0.0167**	-0.0144**	-0.0238***
	(0.00615)	(0.00447)		(0.00640)	(0.00694)	(0.00613)
houses	-0.0700	-0.0427**		-0.0751**	-0.0840*	-0.0677
	(0.0443)	(0.0149)		(0.0305)	(0.0474)	(0.0420)
credit	-0.0389**	-0.0500**		-0.00940	0.00173	-0.0126
	(0.0177)	(0.0190)		(0.0170)	(0.0141)	(0.0148)
Observations	497	212	354	560	451	291
Countries	26	7	18	27	27	27
R-sq	0.513	0.846	0.335	0.560	0.496	0.380
Period	1971-2013	1971-2013	1961-1995	1980-2013	1990-2013	2000-2013
Turning Point	29.21	29.22	27.94	31.4	33.47	-
SLM p-val	.0285	.171	.0261	.0004	.034	-

Notes: Table reports fixed-effects (within) regressions with cluster robust standard errors in parentheses. Dependent variable is the saving rate of the household sector. The bottom part of the table reports the turning points of the inequality effect and the p-values from the Sasabuchi-Lind-Mehlum (SLM) test for a hump-shaped relationship. Column (1) drops the top and bottom 5% of saving and inequality; (2) includes only the G7 economies; (3)-(6) draw on different time periods. Ginis are sourced from the SWIID. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Semiparametric regressions

In this section, we allow inequality to take a flexible functional form by estimating a semiparametric regression model:

$$\text{saving}_{it} = f(gini_{it}) + \beta'\text{X}_{it} + \alpha_i + \epsilon_{it}, \tag{3.2}$$

where the control variables X_{it} enter the model linearly and $f(gini_{it})$ denotes an unknown function of the Gini. Our panel data regressions are based on Baltagi and Li (2002), whose estimator was build into *Stata* by Libois and Verardi (2013). Essentially, the estimator relies on a first difference transformation to expunge the fixed effects (α_i) and uses OLS to estimate the parametric part of the regression equation. Afterwards $f(gini_{it})$ is estimated via a B-spline regression model. Moreover, we apply the semiparametric estimator by Robinson (1988) with the pooled data. Robinson's estimator, which was implemented in *Stata* by Verardi and Debarsy (2012), partials out the parametric part of the regression equation and runs kernel regressions on the residuals. As non-parametric estimations are sensible to outliers, we use the full set of control variables (and thus the narrower sample) for all semiparametric regressions.

Figure 3.3 pictures the non-parametric part of these estimations, while the results for the linear part of the model are shown in Table 3.10 in the appendix. The upper graph illustrates the estimated relationship from Robinson's semiparametric estimator, which we use with an Epanechnikov kernel function and cluster robust standard errors. In line with a corresponding pooled OLS estimation of a quadratic regression model (see, Table 3.10), Robinson's semiparametric estimator shows a hump-shaped relationship and a similar turning-point, lying roughly at a Gini of around 27.

The form of the relationship is less clear when it comes to the semiparametric fixed effects estimator. The lower part of Figure 3.3 indicates a concave relationship when the power of the B-splines is set to d(3). Yet in the default specification, with a power of d(4), the graph hints towards a 3rd order polynomial form, where saving tends to rise again at very high levels of inequality. A direct inclusion of a cubic term into a parametric fixed effects or pooled OLS model, however, yields no significant results (see, Table 3.10 in the appendix).[26]

[26] As Baltagi and Li's (2002) estimator relies on a first difference transformation, while the standard fixed effects estimator is based on demeaning, results are not directly comparable.

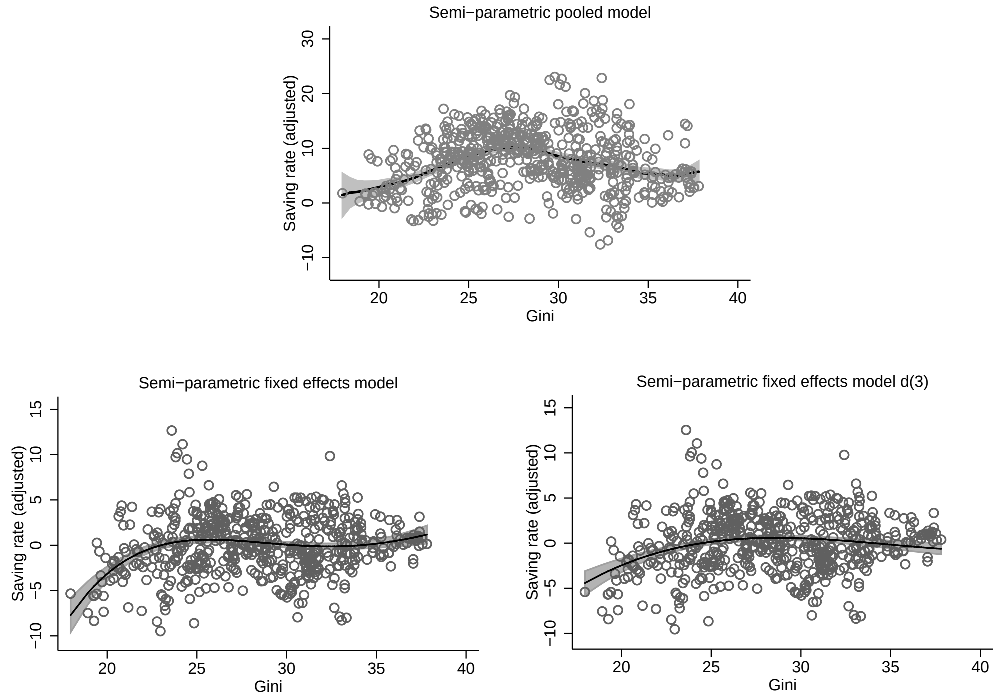


Figure 3.3: Partial fit of the relationship between saving and inequality.
Notes: The points in each graph are partial residuals for the household saving rate; saving rates have been adjusted for the effects of the linear control variables (see, Eq. 3.2). Partial residuals of the fixed effects regressions are centered around the mean. Shaded areas correspond to 90% confidence intervals.

In sum, semiparametric regressions yield no strong evidence against a quadratic functional form. As the simple fixed effects estimator is more efficient than the semiparametric alternatives, we regard the findings of this section as sufficient to confirm the presence of a hump-shaped pattern between inequality and saving. Nonetheless, we will later discuss some arguments why saving rates may increase with inequality, when inequality is already very high.

3.5.3 Interactions with credit availability, financial development, and different time periods

Interactions with credit availability and financial development

Along the lines of previous studies (Smith, 2001; Alvarez-Cuadrado and El-Attar Vilalta, 2012) we suppose that the relation between inequality and saving may depend on the state of financial market development. The idea is that poorer households, who face a decline in relative income, need credit financing to keep up with rising consumption of the rich. Easy credit availability could thus be a precondition for expenditure cascades: In countries with liberalized financial markets expenditure cascades may dominate the link between inequality and saving, whereas Keynesian effects may prevail where credit financing is scarce.

To test for the presence of such a conditional effect we complement our baseline regression model with an interaction term, which is the product of inequality and a moderator variable measuring either credit availability or financial market liberalization:

$$\text{saving}_{it} = \alpha + \beta_1 \text{gini}_{it} + \beta_2 \text{credit}_{it} + \beta_3 \text{gini}_{it} \times \text{credit}_{it} + \beta' \text{X}_{it} + \alpha_i + \lambda_t + \epsilon_{it} \qquad (3.3)$$

The first two Columns of Table 3.8 report the estimates for this interaction model (excluding and including the country fixed effects) with the ratio of private credit to GDP as the moderator variable (credit). Indeed, both the pooled OLS model of Column (1) and the fixed effects model of Column (2) yield strong evidence for a significant interaction effect. In both equations the product of Gini and credit is significantly negative, while the Gini has a significantly positive coefficient.[27]

Differentiating the equation in Column (2) with respect to inequality yields the marginal effect of inequality across different levels of credit, pictured as a downward sloping line in Figure 3.4. While the marginal effect of inequality on household saving is positive at low and average levels of credit, it becomes negative at a credit ratio of 130 percent. However, the surrounding 90% confidence intervals indicate that inequality exerts a significantly positive effect only with credit below 87% of GDP. Moreover, inequality only

[27] We estimated the model of Column (2) with six alternative measures of income inequality: $gini_{lis}$, *the Atkinson Index, S80/S20, P90/P10, P90/P50, and top1inc.* In five of these models the interaction between inequality and credit is negative and highly significant. Only the income share of the top 1% is not significant. Results can be found in the online appendix.

Table 3.8: Interactions

	(1) POLS	(2) FE	(3) POLS	(4) FE	(5) FE	(6) FE
gini	1.146***	0.958***	1.332***	0.390	3.325***	2.499***
	(0.322)	(0.295)	(0.371)	(0.338)	(0.971)	(0.732)
$gini^2$					-0.0532***	-0.0408***
					(0.0163)	(0.0120)
credit	0.311***	0.185***				-0.0195
	(0.0910)	(0.0459)				(0.0163)
ginixcredit	-0.0116***	-0.0074***				
	(0.00297)	(0.00159)				
finreform			0.351*	0.157		
			(0.170)	(0.109)		
ginixfinreform			-0.0161***	-0.00614		
			(0.00543)	(0.00378)		
credithigh					17.71	
					(21.90)	
ginixcredithigh					-0.968	
					(1.544)	
$gini^2$xcredithigh					0.0107	
					(0.0268)	
postcrisis						37.64
						(40.64)
ginixpostcrisis						-2.020
						(2.616)
$gini^2$xpostcrisis						0.0269
						(0.0417)
Observations	616	616	451	451	648	616
Countries	27	27	21	21	27	27
R-sq	0.430	0.612	0.509	0.539	0.595	0.609

Notes: Table reports pooled OLS (POLS) and fixed-effects (FE) regressions with cluster robust standard errors in parentheses. Dependent variable is the saving rate of the household sector. Control variables (depend, incgrow, interest, fiscal, equities, houses, ln(gdppc), infl) are omitted for clarity. Ginis are sourced from the SWIID. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

becomes significantly negative, when credit is above 165% of GDP, a threshold which for example the United States exceed since the early 2000s.

A possible problem arising from the use of the credit ratio as an explanatory or moderator variable is that it could be endogenous with respect to the saving rate. To circumvent this problem, we employ the financial reform index, composed by Abiad et al. (2010), as a measure of credit market liberalization in Columns (3) and (4). Given that the financial reform index (*finreform*) is a de jure measure, it is free of endogeneity concerns. Yet, being based on sub-indices on subjects like capital account restrictions, interest rate controls, etc., the index is merely a rough proxy of credit availability.

When we substitute credit with *finreform* in the pooled OLS model of Column (3),

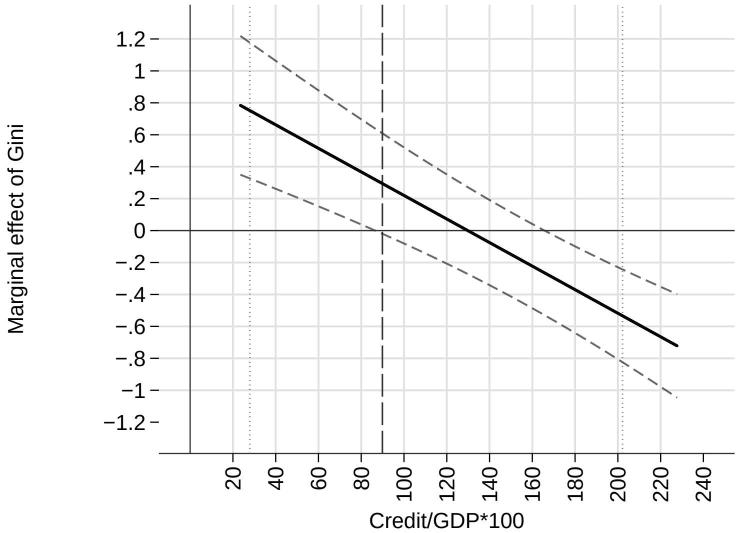


Figure 3.4: Marginal effect of inequality on saving at different levels of credit availability
Notes: Values are calculated using the results of Column (2) of Table 3.8. The downwards sloping line plots the marginal effect of inequality. Surrounding dashed lines represent the 90% confidence intervals. Vertical lines indicate the distribution of the credit to GDP ratio in the sample: dotted lines mark the first and 99th percentiles, the dashed line marks the median value.

the signs of the coefficients of inequality and the interaction term remain unchanged. Apparently, with highly regulated financial markets (low index values) a positive marginal effect of inequality prevails, but decreases and finally becomes negative with increasing financial liberalization (high index values). Nonetheless, in the fixed effects model of Column (4) the interaction effect is insignificant, which is not surprising given that most of the index variation stems from differences across countries.

As the effect of inequality depends on credit availability, it is questionable whether the concave and hump-shaped relationship is also robust to different states of financial development. To test for the presence of heterogeneous effects, we create a dummy variable, *credithigh*, which we set as 1 for values of credit to GDP above the sample median of 90%.[28] Then we effectively split our sample into a low-credit and a high-credit subsample by estimating the following model:

$$\text{saving}_{it} = \alpha + \beta_1 \text{gini}_{it} + \beta_2 \text{gini}_{it}^2 + (\beta_3 \text{gini}_{it} + \beta_4 \text{gini}_{it}^2 + \beta_5) \times \text{credithigh}_{it} + \beta' \text{X}_{it} + \alpha_i + \lambda_t + \epsilon_{it} \tag{3.4}$$

Column (5) of Table 3.8 reports our estimates for this model. The effect of inequality in country-years with a low level of credit can be directly seized via β_1 and β_2, which indicate

[28]The estimated coefficient of credithigh (-1.012) is insignificant (p-value: 0.131) in a model where *credithigh* serves as an additional regressor, but not as a moderator variable.

a significant hump-shaped relationship. At high-levels of credit $\beta_1+\beta_3$ and $\beta_2+\beta_4$ measure the inequality-saving relationship, indicating a concave relationship that is somewhat less pronounced than in the low-credit subsample.

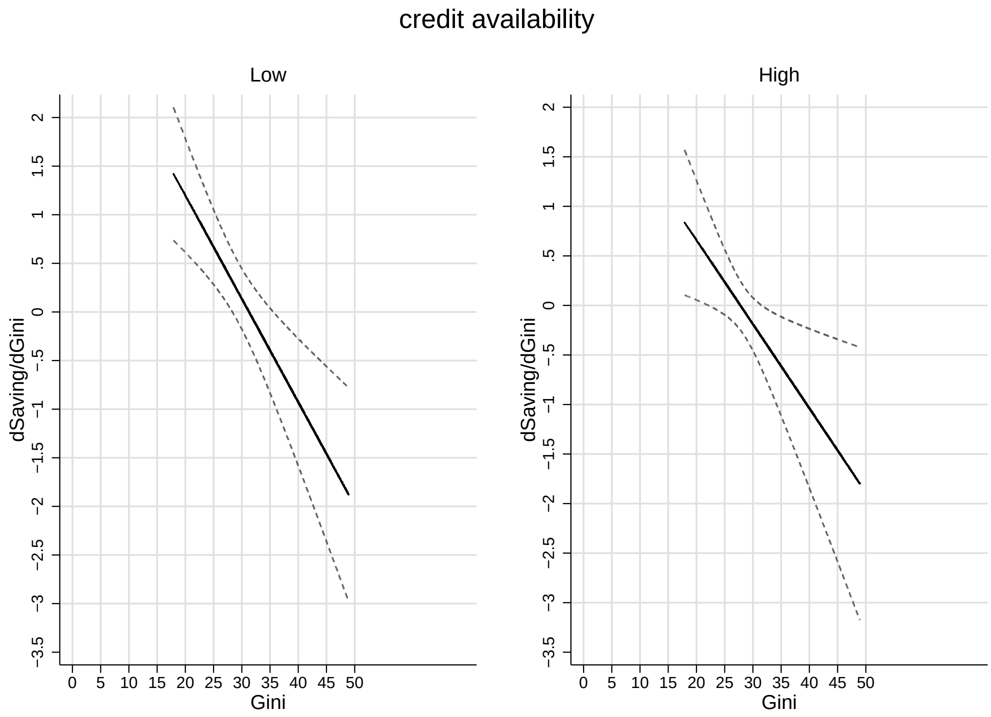


Figure 3.5: Marginal effect of inequality on saving with low and high credit availability (below and above 90% of GDP)
Notes: Values are calculated using the results from Column (5) Table 3.8. The downwards sloping line plots the marginal effect of inequality at different levels of inequality. Surrounding dashed lines represent the 90% confidence intervals.

Based on the results from Column (5), Figure 3.5 illustrates the marginal effect of inequality at low and high levels of credit together with the 90% confidence intervals.[29] It shows that the Gini at which the marginal effect of inequality turns from positive to negative is somewhat higher in the low-credit group.[30] Moreover, very tight 90% confidence intervals in the low-credit subsample indicate that inequality exerts a significant positive effect on saving at a wider range of inequality values. Within the high-credit group inequality yields a significantly positive effect only at very low levels of inequality and becomes significantly negative for values of the Gini above 33.

[29]Generating this figure we benefited from the code provided by Arcand et al. (2015)
[30]The turning point is 31 in the low-credit group and 28 in the high-credit group.

Altogether, we find that the relation between inequality and saving tends to be positive with low credit availability and negative with high credit availability. Nonetheless, a hump-shaped relationship between inequality and saving prevails in both low and high-credit environments.

Inequality and saving after the financial crisis

Given that the risks of subprime lending to poorer households became obvious with the 2008-10 Global Financial Crisis (see, e.g. Rajan, 2010), the ability and willingness of poorer households to engage in expenditure cascades may have decreased. Thus the negative part of the hump-shaped relationship between inequality and saving may have vanished in the post-crisis period.

To test for this supposition we create a dummy variable (*postcrisis*), which we set as 1 for all observations after 2007. Then we effectively split our sample into a pre-crisis and a post-crisis subsample by estimating a nested regression model, similar to Equation 3.4.[31]

The results for $gini \times postcrisis$ and $gini^2 \times postcrisis$ in Column (6) of Table 3.8 indicate that the estimated coefficients of inequality have declined after the outbreak of the crisis. Yet the interacted terms are statistically insignificant and smaller than the main effects. Figure 3.6 plots the marginal effects of inequality received from the estimated equation. It shows that before 2008 inequality had a significantly positive effect on saving if the value of the Gini was below 25, a null effect at a Gini of around 30, and a significantly negative effect at Ginis above 35. In the post-crisis period, however, inequality never exerted a significant effect.

Summing up, the distinction between pre- and post-crisis periods confirms our supposition that a negative effect of inequality on household saving vanished in the wake of the financial crisis. Yet, the insignificance of the relationship between inequality and saving could as well be due to the loss of efficiency, given the small number of observations in the post-crisis period.

[31] The most recent observations in our panel are from 2013, so that the post-crisis dummy marks all observations from the 2008 to 2013.

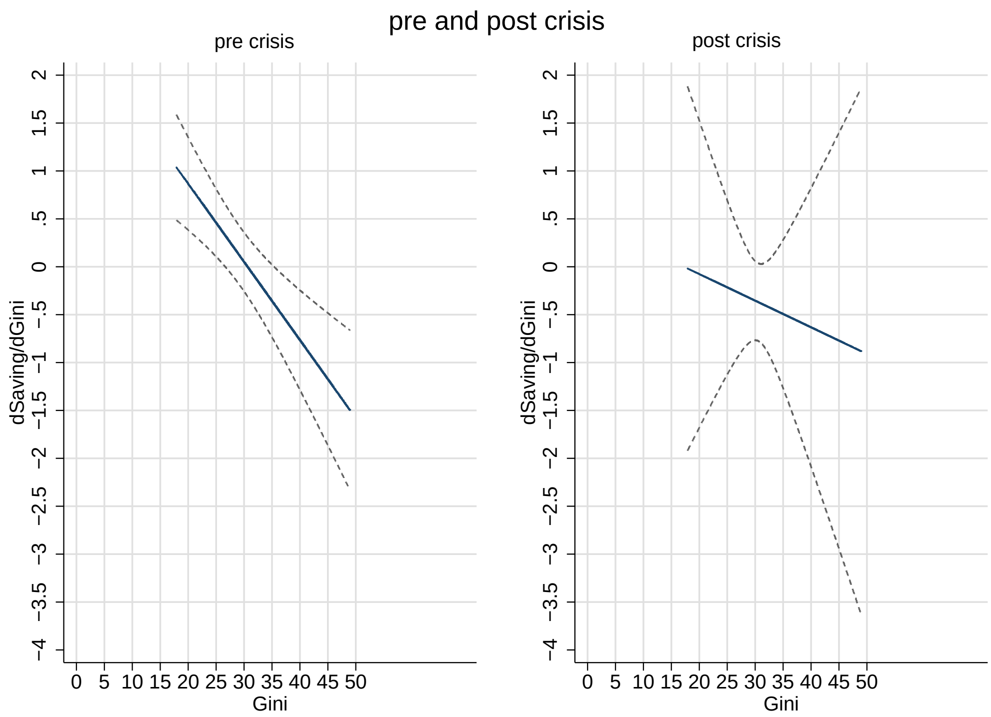


Figure 3.6: Marginal effect of inequality on saving before and after the Global Financial Crisis (before and after 2008)
Notes: Values are calculated using the results from Column (6) Table 3.8. The downwards sloping line plots the marginal effect of inequality at different levels of inequality. Surrounding dashed lines represent the 90% confidence intervals.

3.5.4 Private saving, national saving, and the current account

Finally, we analyze whether the effect of inequality on household saving transmits to broader measures of saving and the current account balance. Although our theories of interest refer to household behavior, the household saving rate would be too narrow if richer households maintain a large volume of saving within incorporated enterprises. As it includes saving from both the household and the corporate sector, the use of private saving rates could thus be beneficial. Following previous cross-country studies on inequality and saving, we also look at national saving rates, which include saving by the government. National saving could be of interest as it measures the total amount of saving in the economy. Yet, its application is problematic if fiscal policy exerts offsetting effects.

Referring to studies that motivate this chapter, we finally check whether the link between inequality and saving transmits to the current account. Being the balance between national saving and investment, we would expect that inequality has a similar influence on the current account as it has on saving.

Table 3.9: Alternative dependent variables

	(1) Household-Saving	(2) Private-Saving	(3) National-Saving (net)	(4) National-Saving (gross)	(5) Current Account
gini	3.057***	2.755**	3.086***	1.894***	2.602***
	(0.865)	(1.060)	(0.843)	(0.494)	(0.709)
gini^2	-0.0547***	-0.0461**	-0.0497***	-0.0333***	-0.0436***
	(0.0123)	(0.0167)	(0.0138)	(0.00811)	(0.0123)
depend	-0.814***	-0.351*	-0.650***	-0.277*	0.131
	(0.279)	(0.185)	(0.164)	(0.142)	(0.122)
incgrow	0.296***	0.316***	0.470***	0.247***	-0.140*
	(0.0622)	(0.0854)	(0.0644)	(0.0830)	(0.0711)
interest	-0.0405	-0.0522	-0.282***	-0.339***	-0.00218
	(0.179)	(0.109)	(0.0938)	(0.115)	(0.120)
fiscal	-0.524***	-0.360***			0.0112
	(0.0964)	(0.0779)			(0.0665)
Observations	517	517	517	517	517
Countries	25	25	25	25	25
R-sq	0.439	0.310	0.419	0.238	0.0939
Turning Point	27.93	29.88	31.06	28.43	29.83
CI 90%	[22.68; 30.91]	[24.91; 33.03]	[28.18; 34.60]	[24.56; 31.89]	[26.93; 33.75]
Slope: gini_{min}	1.09**	1.1**	1.3***	.69***	1.03***
Slope: gini_{max}	-2.31***	-1.76***	-1.78***	-1.37***	-1.67***
SLM p-val	.0104	.0148	.0018	.0025	.0022

Notes: Table reports fixed-effects (within) regressions with cluster robust standard errors in parentheses. The bottom part of the table reports the turning points of the inequality effect and the results of the Sasabuchi-Lind-Mehlum (SLM) test for a hump-shaped relationship. CI-90% denotes the 90% Fieller confidence intervals for the turning point. Slopes at gini_{min} and gini_{max} are uniformly measured at ginis of 18 and 49. Ginis are sourced from the SWIID. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.9 presents the results of regressions for these alternative dependent variables. To enhance comparability, each Column draws on a uniform sample of 517 observations. The regressors are identical to the small fixed effects model from our baseline table. Yet, as it is too closely related to public saving, which is part of the dependent variable, we drop the fiscal balance in the regressions for national saving.[32]

As a benchmark reference, Column (1) repeats the baseline household saving regression, which is now based on the uniform sample. Column (2) reports results for the net private saving rate. Both Columns (3) and (4) cover national saving rates: In Column (3) national saving is measured net of fixed capital depreciation, in line with the concept that

[32] One could as well argue that the fiscal balance is a direct component of the current account balance. Yet, because it is frequently used in the current account literature, we keep the fiscal balance as a regressor in Column (5).

we adopt throughout this chapter. Yet most previous studies use gross national saving rates, which we utilize in Column (4). Finally, Column (5) reports results for the current account balance. The Data Appendix describes the sources and derivations of the new dependent variables.

For each saving aggregate our results indicate a non-monotonic effect of inequality and the SLM-Test always confirms the existence of a hump-shaped relationship. Moreover, the shape of the relationship is always similar, with minor differences: For net private saving and even more so for net national saving, the effect of inequality appears to be positive at a wider range of Ginis. Yet, for gross national saving, the turning point of the hump-shaped relationship is again close to the peak value from the household saving regression. Even for the current account balance the effect of inequality is similar to the one we know from the household saving regressions. Apparently, the current account increases with rising inequality, if inequality is low, whereas it tends to decrease, when the Gini becomes larger than 30.[33]

In sum, the impact of inequality on household saving rates appears to transmit to broader saving aggregates. Moreover, although the drivers of current account balances are not the primary focus of this chapter, our results also hint that inequality affects the current account in a non-monotonic way.

3.6 Conclusion

This chapter shows that the marginal effect of inequality on saving is decreasing in the level of credit availability and financial liberalization. Above all, however, we find that the relationship between inequality and aggregate saving is hump-shaped, meaning that with higher levels of inequality an initially positive marginal effect of inequality decreases and eventually becomes negative.

An explanation for the decreasing marginal effect of inequality could be given by a non-linear adaption in household consumption behavior: If inequality only becomes gradually visible, the saving rates of poor and middle-class households possibly remain unchanged, while inequality is still rising from a low level. Thus aggregate saving would initially be dominated by an increasing income share of households with a high propensity

[33]The hump-shaped relationship also prevails with the full set of covariates and an unrestricted sample. Results are available on request.

to save. As inequality rises further, this positive effect on saving could be increasingly compensated by a changing behavior of households from the middle and lower ranks of the income distribution. When inequality becomes more and more visible, the incentive to engage in conspicuous consumption rises until the decrease in saving of poorer households dominates in aggregate.

Moreover, at high levels of inequality, further gains in inequality could increasingly result from a decline in the real income of poorer households. At some point, income may fall below a level that suffices to finance saving plus socially acceptable minimum consumption. Income losses will then be compensated by a reduction of the saving rate. When the latter starts to offset the direct effect from rising income concentration, the marginal effect of inequality on aggregate saving decreases and after some point becomes negative.

Our findings suggest that the inequality driven decrease in saving, at high levels of inequality, appears to have vanished since the outbreak of the global financial crisis. Even if inequality continues to rise, for poorer households a permanent compensation of income losses via credit financing is hardly conceivable. Consequently, as soon as saving rates of low and middle income households have reached a floor at zero, it is likely that the Keynesian effect of a rising income concentration at the top will dominate.

3.7 Appendix to chapter 3

Appendix A1: Data Description

Household saving rate (saving$_{hh}$): Is sourced from the OECD Economic Outlook (EO) and National Accounts (NA) Databases. The OECD calculates saving by subtracting household consumption expenditure from household disposable income plus the change in net equity of households in pension funds. Saving is reported as net of depreciation. The saving rate is calculated with saving in the numerator and the net household disposable income, plus the change in the net equity of households in pension funds, in the denominator. The formula for the saving rate in the System of National Accounts is (see, Catte and Boissinot, 2005):

$$s_t = S_t/YD_t = (YD_t - C_t)/YD_t = (r_t W_{t-1} + Y_t - T_t - C_t)/(r_t W_{t-1} + Y_t - T_t)$$

where s denotes the ratio of saving S, to disposable income, YD, and C is the value of consumption. Disposable income consist of labour income, Y, and capital income, rW, minus taxes and transfers, T.

Gross national saving (saving$_{gross}$): The World bank calculates gross saving (% of GDP) as gross national income less total consumption, plus net transfers.

Net national saving (saving$_{net}$): Net saving (% of GDP) is sourced from the OECD NA Database. It is defined as the difference between disposable income and final consumption expenditure plus an adjustment for the change in pension entitlements. Net saving is reported net of fixed capital depreciation.

Private saving (saving$_{prvt}$): Is calculated as net national saving less net saving of general government (% of GDP), which is also sourced from the OECD NA Database.

Current account: The current account balance (% of GDP) is sourced from the OECD EO database.

Gini coefficients: Our preferred measure of income inequality is the Gini of net incomes (i.e. disposable household income). Ginis are either taken from the Key Figures of the Luxembourg Income Study (LIS) or from the Standardized World Income Inequality

Database (SWIID, Version 5.0, released in October 2014) generated by Solt (2009, 2016). The SWIID is based on the UN World Income Inequality Database (WIID), and several other cross-country inequality datasets, data provided by national statistical offices, and scholarly articles. As the source data is not directly comparable it is transformed and adjusted in several steps, described in Solt (2016). A very rough overview of the standardization procedure can be given as follows: 1. The data is sorted into categories by welfare definitions and by equivalence scale. Ginis of net and market inequality on the basis of household adult equivalent income from the Luxembourg Income Study (LIS) are added as a baseline, generating a dataset in which each country-year observation has data entries in at least one of thirteen categories. 3. Ratios between the variables in different categories are estimated as a function of country-decade, country, region and development status through various regression models. In further steps eleven series of estimates, comparable with the LIS net-income data, are calculated and combined into a single variable. 4. Possible measurement errors are corrected by using five-year weighted moving averages on all data points except those taken from the LIS and certain time periods.

S80S20: The S80/S20 ratio is the income share of the top quintile divided by the income share of the bottom quintile. Income shares are sourced from the World Bank's WDI database.

P90P10 and *P90P50*: Percentile ratios come from the Key Figures of the Luxembourg Income Study. They are based on disposable household income.

Top 1% income share (top1inc): The data on top incomes is sourced from the World Top Incomes Database (WTID) by Atkinson et al. (2015). Whenever possible, we chose the standard series, which were given without any reference to divergent tax units or data sources. Exceptions are: The UK and Denmark where the data measures the income share of adults; and Finland where numbers are based on the income distribution survey (IDS). In contrast to our Gini data, top income shares are based on gross incomes before taxes and transfers. Series are mostly expressed as percentage of total income excluding capital gains, but there are also some differences in income definition, which we ignore in order to maintain a reasonably wide dataset. Due to these and other limitations on cross-country comparability, the inclusion of country fixed effects is crucial in regressions with top income shares.

Old-age dependency ratio (depend): Is obtained from the World Bankâs WDI database. It is defined as the share (in %) of the population aged 65 and older over the working-age population (people between 15 and 64).

Real growth rate of disposable income per capita (incgrow): Real household disposable income was taken from the OECD Economic Outlook and the OECD National Accounts Database. Growth rates reflect year on year variations.

Real interest rate (interest): The real interest rate is calculated by subtracting the inflation rate from the interest rate on long-term government bonds, which is sourced comes from the OECD Economic Outlook.

Fiscal balance (fiscal): The fiscal balance (cash surplus/deficit % of GDP) is collected from the WDI database, except when data from the OECD EO database is available (NLGQ: Government net lending, as a percentage of GDP)

Ln GDP per capita (ln(gdppc)): Is the natural logarithm of per capita GDP sourced from the OECD National Accounts Database. GDP is measured in US Dollars (â000s) at constant prices and constant PPPs. The OECD base year is 2010.

Inflation rate (infl): The CPI inflation rate is sourced from the OECD Main Economic Indicators and expanded with World Bank WDI data.

Real house price development (houses): A quarterly index of real house prices is retrieved from the OECD Housing Prices database. We calculate the year on year growth rate on the annual averages of the quarterly data.

Real equity return (equities): Is measured as the yearly performance of the main national share price indices, sourced from the OECD Main Economic Indicators, minus the CPI inflation rate. According to the OECD data description âthe share indices are targeted to be national, all-share or broad, price indices.â

Financial depth (credit and finreform): *Credit*, is the ratio (expressed in %) of private credit to GDP, from the WDI database. *Finreform* is the Financial Reform Index provided by Abiad et al. (2010). It is an institutional index that measures the overall level of financial market regulation on the basis of several sub-indices: Credit directions and requirements on central bank reserves, interest rate controls, entry barriers, aggregate credit ceilings, state ownership in the banking sector, capital account restrictions, prudential regulation and banking supervision, and securities market policies. The index ranges between 0 and 100. Higher values of the index imply more liberalized financial markets.

Countries in the sample are: Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Japan, Korea Rep., Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States.

Appendix A2: Semiparametric and 3rd order polynomial regressions.

Table 3.10: Semiparametric and 3rd order polynomial regressions

	(1) Semi-POLS	(2) Semi-FE	(3) Semi-FE	(4) POLS	(5) POLS	(6) FE
gini				4.805***	16.54	6.082
				(1.097)	(10.79)	(6.440)
$gini^2$				-0.0849***	-0.502	-0.157
				(0.0192)	(0.389)	(0.234)
$gini^3$					0.00486	0.00123
					(0.00458)	(0.00275)
depend	-0.127	0.0489	0.0405	-0.168	-0.133	-0.687***
	(0.169)	(0.171)	(0.172)	(0.154)	(0.157)	(0.186)
incgrow	0.645***	0.339***	0.338***	0.659***	0.658***	0.384***
	(0.117)	(0.0277)	(0.0279)	(0.123)	(0.120)	(0.0641)
interest	-0.0500	0.0650	0.0690	-0.137	-0.0590	-0.0874
	(0.207)	(0.0720)	(0.0739)	(0.190)	(0.210)	(0.154)
fiscal	-0.449***	-0.231***	-0.229***	-0.496***	-0.471***	-0.425***
	(0.160)	(0.0633)	(0.0627)	(0.155)	(0.156)	(0.0943)
ln(gdppc)	-0.587	-13.12***	-13.08***	0.205	-0.169	-1.246
	(2.978)	(3.063)	(3.041)	(2.889)	(2.998)	(4.119)
infl	0.512**	0.149	0.151	0.470**	0.543***	0.105
	(0.206)	(0.0916)	(0.0924)	(0.186)	(0.191)	(0.115)
equities	0.0176*	-0.00472*	-0.00447*	0.0183*	0.0188*	-0.0131**
	(0.0102)	(0.00261)	(0.00258)	(0.0103)	(0.0105)	(0.00497)
houses	-0.113*	-0.0457***	-0.0463***	-0.120*	-0.118*	-0.0717**
	(0.0618)	(0.0144)	(0.0143)	(0.0597)	(0.0615)	(0.0275)
credit	-0.00952	0.00169	0.00195	-0.0106	-0.00805	-0.0148
	(0.0178)	(0.00662)	(0.00657)	(0.0178)	(0.0176)	(0.0179)
Observations	616	581	581	616	616	616
Countries	27	27	27	27	27	27
R-sq	0.338	0.408	0.408	0.386	0.391	0.582

Notes: Dependent variable is the saving rate of the household sector. Column (1)-(3) report the linear part of semiparametric models, estimated with Robinson's semiparametric regression estimator (Column 1) and the Baltagi and Li fixed effects estimator (Columns 2 and 3). Columns (4)-(6) report pooled OLS (POLS) and fixed-effects (FE) regressions with cluster robust standard errors in parentheses. Ginis are sourced from the SWIID. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Chapter 4

The Effects of Inequality and Redistribution on Economic Growth: What are the Transmission Channels?

4.1 Introduction[1]

In his famous book *"Equity and Efficiency: The Big Tradeoff"*, Okun (1975) points out that the trade-off between social justice and economic efficiency *"[...] plagues us in dozens of dimensions of social policy"*. Okun's notion led to the widespread belief that public redistribution via taxes and transfers creates disincentives and inefficiencies that Okun compares to a *"leaky bucket"*, with money lost whenever transfers are made from the rich to the poor. However, empirical evidence for the existence of such a trade-off is rather ambiguous.

The literature at hand can be divided into two distinct groups. One branch examines the link between inequality and growth, while the other studies the growth effects of redistributive taxes and social transfers. This chapter follows a novel approach by simultaneously exploring the growth effects of both income inequality and effective public redistribution, with the latter computed as the difference between market and net income Gini coefficients. We find that a high level of inequality reduces GDP growth, but its remedy—redistribution via taxes and transfers—is detrimental to growth as well. Thus, the direct negative effect of redistribution offsets its indirect positive growth effect from reduced net inequality. Taken together, this means that at a given level of market inequality, the impact of redistribution on economic growth is insignificant. However, the growth effects of both inequality and redistribution depend on the development level of the economy. Whereas redistribution—on aggregate—fosters growth in developing countries, it seems to have a rather impedimental effect in advanced economies. To study these effects in greater detail, we explore the transmission channels through which inequality and redistribution affect economic development. In fact, recent studies on the inequality-growth nexus mainly focused on reduced form evidence, neglecting the mechanisms behind the identified effects. Our results suggest that higher inequality is negatively related to education and yields an increase in the fertility rate. Both effects are particularly prevalent in the presence of limited access to capital and can be mitigated by public education spending. Meanwhile, the direct negative effects of redistribution are mainly due to a decrease in investment and an increase in fertility.

[1]This chapter is based on joint work with Klaus Gründler. An early version appeared as Gründler and Scheuermeyer (2015). The present version has benefited from the comments of an anonymous referee of the *Journal of Macroeconomics* where it is currently under third round review.

How do these findings relate to earlier studies on the topic? Whereas cross-country analyses tend to find a negative relationship between income inequality and economic growth, the results have become ambiguous since the advent of panel data methods.[2] Particularly, Li and Zou (1998) and Forbes (2000) contradict previous findings by detecting a positive impact of inequality on economic growth. In contrast, Barro (2000) yields little indication of a uniform relationship between inequality and growth, as he finds a negative effect of inequality in developing countries and a positive effect in richer economies. Castelló-Climent (2010) confirms this interaction with the development level, but finds an overall negative growth effect of income and human capital inequality. Focusing on the use of consistently measured inequality data, Knowles (2005) finds a negative effect of Ginis from household expenditures, but not of Ginis from gross incomes. Voitchovsky (2005) enriches the debate by looking at the shape of the income distribution. The study concludes that growth is promoted by inequality at the top end of the income distribution, but weakened by inequality at the bottom end. Finally, Halter et al. (2014) emphasize the time dimension of the inequality-growth relationship by showing that higher inequality fosters growth in the short term, but hampers growth in the medium to long run. Hence, one explanation for the inconclusiveness of the literature is that estimates based on time-series variations pick up positive short-run effects of inequality, whereas methods which also exploit cross-country variations capture its negative impact in the medium to long run.

The empirical evidence for the growth effects of redistributive fiscal policy is also divided. Using specific fiscal policy instruments to proxy the extent of redistribution—such as marginal tax rates or the amount of social spending—, earlier studies tend to find a negligible or slightly positive impact on growth (see, e.g., Perotti, 1996). In light of these findings, Lindert (2004) suggests that large welfare states have come up with methods to minimize the negative incentive effects and deadweight losses from taxes and social spending. In contrast, a study by Muinelo-Gallo and Roca-Sagalés (2013), which uses panel data from 21 high-income OECD countries, shows that distributive expenditures and direct taxes produce significant reductions in inequality, but also in GDP growth.

So far, a lack of meaningful and comparable data limits the exploration of the growth effects of inequality and redistribution. First, with regard to the relationship between

[2] The empirical growth literature of the 1990s is comprehensively reviewed in Aghion et al. (1999).

inequality and growth, several studies (Knowles, 2005, Atkinson and Brandolini, 2009) highlight that mixing Ginis from different income definitions or applying simple transformations to make them more comparable is inappropriate but nevertheless a common approach in the literature. Meanwhile, attempts to work with consistently measured inequality data have so far been restricted to a very narrow selection of countries and years (Knowles, 2005, Voitchovsky, 2005), imposing the risk that findings are due to sample selection rather than different income definitions.[3] Second, regarding the effect of redistribution on growth, most studies use fiscal policy variables to measure the extent of public redistribution. Yet the size of taxes and transfers tells little about their progressivity, meaning that the redistributive impact of specific fiscal policy measures is unclear and not comparable across countries.

Recent advances in data availability allow us to address these issues by employing a set of inequality data that maximizes comparability for the broadest possible sample of countries and years (Solt, 2016). Applying a flexible missing data algorithm, the Standardized World Income Inequality Database (SWIID 5.0) provides consistent Ginis of net and market incomes for roughly 4,600 country-years. Covering data from 154 countries between 1965 and 2012, our regression sample thus enables investigation of the global relationship between inequality and growth, as well as of the effects at different development levels.

By replacing the ad-hoc fixed adjustments that have long been necessary to generate a large dataset for cross-country research, the SWIID alleviates a general trade-off between data comparability and coverage. Meanwhile, we also scrutinize our results based on a sub-sample of the most reliable observations. In addition, we are among the first to exploit the full potential of the SWIID by directly incorporating data uncertainty into our regression results via multiple estimation tools.

Above all, a clear distinction between inequality before and after taxes and transfers in the SWIID enables measurement of redistribution via calculation of the difference between market-income and net-income Gini coefficients. Thus, we regress growth on effective redistribution rather than relying on rough proxies of redistributive fiscal policies. Although it is commonly applied in sociology and public policy (see, e.g., Lupu and Pontusson, 2011; Van den Bosch and Cantillon, 2008), use of the "pre-post" approach

[3]This problem was already noted by Knowles (2005) and highlighted in a literature survey by Neves and Silva (2014).

for measuring redistribution via the difference between market and net inequality is quite novel in the empirical growth literature. Ostry et al. (2014) utilize an early version of the SWIID to acquire data on effective redistribution. While the study finds little evidence for a significant growth effect of redistribution, it suggests that inequality is an impediment to economic growth. Thewissen (2014) calculates a measure of pre-post redistribution using data from the LIS and the OECD. Based on a panel of high-income countries, the study finds no robust influence of inequality and redistribution on economic performance, but indicates a positive relationship between top income shares and growth.

While subject to some studies based on cross-country data (e.g. Perotti, 1996; Deininger and Squire, 1998; Easterly, 2007; Castells-Quintana and Royuela, 2017), the transmission channels of inequality have been rather neglected in *panel data* studies, a point which is criticized by Galor (2009).[4] Meanwhile, the transmission mechanisms of redistribution are largely unexplored empirically. Hence, we are the first to simultaneously study the transmission channels of both inequality and redistribution via panel data econometrics, thereby accounting for unobserved heterogeneity in both the medium- and the long-run. Our results reveal that income inequality acts mainly via human capital accumulation and the fertility rate, but not necessarily via physical investments. Public redistribution, in contrast, seems to deter investment and to boost the fertility rate. Holding these transmission variables constant, the negative effects of inequality and redistribution on growth vanish. Moreover, the negative impact of inequality on growth is reinforced by credit market imperfections, but attenuated by generous public spending on education. Finally, we provide evidence for the endogenous fiscal policy channel: An increase in market inequality enhances public redistribution, which is why a low level of market inequality is conducive to economic growth.

The chapter is organized as follows: Section 4.2 reviews the main theories on inequality, redistribution, and growth, laying the groundwork for the empirical investigations. Section 4.3 details our empirical specification. Section 4.4 describes the data, focusing on

[4] A recent literature survey (Neves and Silva, 2014) identifies only three panel-data studies that examine the transmission channels of inequality on growth. All of these studies focus on single transmission channels. Drawing on *cross-sectional* data, Castells-Quintana and Royuela (2017) study multiple transmission mechanisms, finding that inequality may trigger both positive and negative effects. As the empirical strategy is based on a control function approach that focuses on the between-country variation, our results are not directly comparable. Yet with regard to the identified negative effect of inequality that accounts for 80% of the total effect estimated by Castells-Quintana and Royuela (2017), our results are complementary.

our measures of inequality and redistribution. The chapter provides an overview of the extent of redistribution across countries and highlights the empirical relationship between inequality and redistribution. We report the baseline results in Section 4.5, followed by an extensive sensitivity analysis. Subsequently, we examine the aggregate effect of public redistribution and investigate its transmission channels. The empirical section closes with an examination of the effects of inequality and redistribution at different levels of development. Section 4.6 concludes.

4.2 The link between inequality, redistribution, and economic growth

Numerous explanations exist for the link between inequality and economic growth.[5] This section consolidates the theoretical approaches into five categories: differential saving rates, credit market imperfections, endogenous fertility, sociopolitical unrest, and the endogenous fiscal policy approach.

4.2.1 Differential saving rates versus credit market imperfections

The classical approach postulates that inequality stimulates growth: Assuming that the marginal propensity to save rises with the income level of individual households (see, e.g., Kaldor, 1955), a concentration of income at richer households increases aggregate saving, which is channeled into investments and thus conducive to growth (Bourguignon, 1981).

However, in the presence of credit constraints and investment indivisibilities an unequal distribution of wealth or income may just as well be detrimental to growth. The credit market imperfections approach, pioneered by Galor and Zeira (1993), suggests that inequality restrains some individuals from exploiting their intellectual potential when credit is not available to cover the direct or opportunity costs of schooling. As the maximum amount of human capital accumulation per person is limited and the returns to human capital are diminishing, an increase in inequality thus reduces both the average

[5] A review of the perspective of the new growth theories can be found in Aghion et al. (1999). Voitchovsky (2009) and Neves and Silva (2014) provide surveys of the more recent theoretical and empirical literature on inequality and growth.

quantity and productivity of human capital. Naturally, a public education system that provides free and high quality schooling can mitigate these negative effects.

A similar argument applies to physical capital investment. Viewing people as potential entrepreneurs who face individual investment opportunities that are bound by decreasing marginal returns and credit market imperfections, the poor may not be able to realize their investment projects while the wealthy overinvest. A rise in inequality would thus reduce the average productivity of physical capital, whereas its quantity may be less affected.

Galor and Moav (2004) provide an intertemporal reconciliation between the *differential saving rates* and the *capital market imperfection* approaches in a unified growth theory. Whereas inequality supports growth by increasing aggregate saving and physical capital investment in early stages of development, inequality is detrimental to growth after human capital accumulation becomes the dominant driver of growth in more developed economies. In advanced economies, however, the effect of inequality eventually diminishes, as credit constraints become less binding.

4.2.2 Endogenous fertility

Initial inequality can be detrimental to growth due to a positive link between inequality and the fertility rate. This transmission channel is closely related to the human capital argument as decisions concerning human capital investment and family size are interrelated (Becker and Barro, 1988). Poor parents may lack the resources to invest in their children's education, particularly if they are excluded from capital markets. Thus their only chance to increase family income (or their old-age support) is to increase household size. In contrast, richer families may face relatively high opportunity costs of raising children. As a result it may be optimal for richer parents to have fewer children and to invest more in human capital, providing their offspring with the prospect of higher lifetime incomes.

Firstly, from this it follows that poor societies tend to have high fertility rates and low levels of education. Secondly, empirical evidence underlines that more inequality is associated with larger fertility differentials between educated and uneducated women (Kremer and Chen, 2002). Building upon this finding, De la Croix and Doepke (2003) emphasize the growth effects of fertility differentials. A mean-preserving spread in income distribution increases the number of poorly educated children from disadvantaged families relative to highly educated children from richer families. As the relative weight of the less educated increases, average human capital is diluted. Moreover, an increase in inequality also raises the total fertility rate, which imposes another negative effect on per capita income growth.[6]

4.2.3 Sociopolitical unrest

Inequality may also deter growth by causing an increase in political and social instability (e.g., Alesina and Perotti, 1996 and Alesina et al., 1996). By increasing risk, political instability exerts a negative effect on investment. Moreover, particularly if inequality is accompanied by low rates of social mobility, individuals may engage in criminal activities instead of work or education. By violating property rights, high crime rates may constitute an impediment to physical investment.

A related argument deals with crony capitalism and nepotism. In highly unequal societies a wealthy upper class may enjoy disproportionate political power. As a consequence, the rich may subvert political or legal institutions, engage in rent-seeking activities, and thus hinder GDP growth (e.g., Glaeser et al., 2003).

4.2.4 Endogenous fiscal policy: market inequality and redistribution

The previously described models are all related to the distribution of disposable income. However, another line of the literature focuses on the growth effects of market inequality and public redistribution. Perotti (1996) named the theory put forward by Bertola (1993), Alesina and Rodrik (1994), and Persson and Tabellini (1994) the *endogenous fiscal policy approach*, and divided it into two successive arguments: The first—called the *political mechanism*—states that an unequal distribution of market incomes creates a high demand for redistributive taxes and transfers via the political voting process (Meltzer and Richard, 1981). The second—the *economic mechanism*—stresses the negative incentive effects of redistribution for physical or human capital accumulation and labor effort.

Two limitations apply to this line of reasoning: First, by stimulating risk taking, entrepreneurship, and innovation a positive insurance effect of public redistribution might offset its negative incentive effect. Second, governments also engage in *indirect redistri-*

[6]See Galor and Zang (1997), Morand (1999), and Kremer and Chen (2002) for models of endogenous fertility arguing along similar lines of reasoning.

bution by providing public goods. This may lead to an increase in social mobility and to an equalization of market incomes, which is not captured in standard measures of redistribution such as taxes and transfers.

4.2.5 Overview

In sum, the testable implications that we draw from theory are that the growth effect of inequality should depend on (i) the degree of credit market imperfection, (ii) the public provision of education, and (iii) the development level. Inequality should exert a negative influence on growth via diminished human capital accumulation and an increase in the fertility rate, while its effect on physical capital accumulation is ambiguous. Finally, a high level of market inequality should be related to a high level of public redistribution, which is most likely detrimental for growth. As many of the proposed transmission channels are offsetting, the net effect of inequality and redistribution remains an empirical question, which we examine in the following sections.

4.3 Empirical model and estimation technique

Our estimation strategy uses 5-year averages of all variables, addressing the long-term perspective of growth theory, the need to smooth short-term fluctuations, and the occurrence of gaps in the data. Employing the model structure developed in a number of recent empirical growth studies (Bond et al., 2001, Voitchovsky, 2005, Halter et al., 2014), the 5-year growth rate evolves as

$$y_{it} - y_{it-1} = (\theta - 1)y_{it-1} + \lambda h_{it} + \gamma \Psi_{it} + \delta R_{it} + \beta \mathbf{X}_{it} + \eta_i + \xi_t + v_{it} \tag{4.1}$$

where y_{it} is GDP per capita of country i ($i = 1, \ldots, N$) at 5-year period t ($t = 1, \ldots, T$), h_t denotes human capital endowment per person, and $\mathbf{X}_t$ comprises an array of control variables. In addition, η_i denotes country-specific effects, ξ_t is a time effect of period t, and $v_{it} \equiv u_{it} - \xi_t - \eta_i$ is the error term of the estimation. The marginal effects of our variables of interest—inequality Ψ_{it} and redistribution R_{it}—are captured by the coefficients γ and δ.

As redistribution and inequality depend on the political and institutional environment of the countries, the disregard of growth-promoting covariates in Equation 4.1 could lead to inconsistency in the estimated coefficients. For this reason, we employ a standard system specification which has proven to explain empirical growth patterns quite accurately in a number of earlier studies (see Barro, 2000, 2003, 2013). However, many of the standard control variables in growth regressions also reflect the transmission channels of inequality and redistribution that we have summarized in Section 4.2. Therefore, a fully specified growth model only identifies the growth effect of inequality and redistribution *beyond* its effect via the standard transmission channels (Galor, 2009). To estimate the full growth effect of inequality and redistribution, we compare the results from the comprehensive growth model with reduced specifications that omit the transmission variables.

Both the differential savings approach and the capital market imperfection theory emphasize that much of the effect of inequality is channeled to growth via education and investment. For this reason, our specification includes average years of schooling (SCHOOLING) and the investment share (INVS). As an additional proxy for human capital, we account for the health level of the population via inclusion of the logarithm of life expectancy at birth, denoted with log(LIFEEX). To measure the effect of the political stability mechanism, we incorporate an index of rule of law and democracy (POLRIGHT) and the inflation rate (INFL) as a proxy for economic uncertainty. The endogenous fertility channel enters into the system via the logarithm of the fertility rate, denoted with log(FERT). Finally, the specification accounts for government consumption (GOVC) and openness (OPEN). The first is assumed to decrease the steady state level of output due to distortions caused in the private sector, while the latter may simultaneously boost growth and inequality due to technological spillovers and increased competition. Data for the control variables are from commonly used sources in growth regressions and are described in appendix A-1.

Controlling for the variables discussed above, we examine whether inequality Ψ_t and the amount of redistribution R_t affect the growth rate. Both variables are strongly interwoven: By simply including redistribution in the model, the estimated parameter captures both the effect from a lower level of inequality (which we expect to be positive) *and* the incentive effects from the redistributional measures employed to achieve the reduction in inequality (which we expect to be negative). The simultaneous inclusion of both variables enables us to isolate these contradicting effects.

Ideally, we would like to expunge the endogenous components from the data using an instrumentation strategy based on strong and valid external instruments in an IV or 2SLS setting. In this case, the empirical strategy would be able to identify causal relationships. However, the empirical literature thus far has not proposed any time-varying external instrument that is i) available for a large number of country-years and ii) fulfills the exclusion restriction.[7] In the absence of a valid external instrument, our analysis employs lagged regressors as internal instruments. This instrumentation strategy is motivated by the argument that the future may not affect the past, thereby ruling out the possibility of a reverse causality, at least if the persistence in the utilized time-series is not too strong.

From the rich palette of dynamic panel estimators that exploit internal instruments, our analysis employs the system GMM estimator to empirically estimate Equation 4.1, which is described in detail in appendix A-2. System GMM has been shown to have better finite sample properties than other commonly used dynamic panel techniques, such as the difference GMM estimator (Arellano and Bond, 1991) or the Anderson and Hsiao (1982) estimator (see Blundell et al., 2000). In addition, this strategy helps to circumvent a dynamic panel bias, which occurs when including a lagged dependent variable in time-demeaning approaches such as within-group estimates (see Nickell, 1981). However, the validity of system GMM relies on some crucial assumptions, particularly the Arellano and Bover (1995) conditions. To detect possible violations of these assumptions, we conduct Hansen's J and Difference-in-Hansen tests along with each regression.[8] Moreover, to respond to the growing concern of weak instrumentation in empirical growth studies, we follow Bazzi and Clemens (2013) and Kraay (2015) by performing a number of weak instrument diagnostics to ensure consistency and to guarantee that the estimated parameters are unbiased.

The system GMM estimator uses lagged variables as internal instruments for endogenous regressors. To avoid arbitrary assumptions on exogeneity, we treat all independent variables as endogenous, as is common in the literature. This, however, potentially leads to a large number of instruments. Yet, a large set of instruments possibly overfits the

[7] In fact, Bazzi and Clemens (2013) stress that violations of the exclusion restriction in numerous growth regressions focusing on external instruments raise doubts about the obtained results. Among the few attempts to instrument inequality with external instruments, the most promising study is Easterly (2007), which proposes instrumenting inequality with agricultural endowment. However, this instrumentation strategy is not applicable when using panel data that contains both affluent and developing countries over a long time-span.

[8] A more detailed description of the estimator in the context of the empirical application can be found in Bond et al. (2001) and Roodman (2009b).

instrumented variables, which may fail to expunge the endogenous components and may bias parameter estimates towards those from noninstrumenting estimators. To tackle this problem, we follow a two-sided strategy: First, we follow the advice of Roodman (2009a), restricting the instrument matrix by utilizing second lags of the variables in levels as instruments for the difference equation and first lags of the differentiated variables for the level equation.[9] Second, we use principal component analyses to reduce the instrument count (Bai and Ng, 2010; Kapetanios and Marcellino, 2010). This strategy further allows us to exploit information from a larger lag structure. As criteria to model the number of components, we attend to Hansen's J-test, the Kaiser-Meyer-Olkin measure of sampling adequacy (Kaiser, 1974), and the portion of the variance that is explained by the utilized components. A detailed illustration of our moment conditions is provided in appendix A-2.

In principle, our specification can be estimated using one-step or two-step GMM. Whereas one-step GMM estimators use weight matrices independent of estimated parameters, the two-step variant weights the moment conditions by a consistent estimate of their covariance matrix. The two-step procedure is asymptotically more efficient (Bond et al., 2001), but the computed standard errors may be downward biased in small samples. We therefore rely on the Windmeijer (2005) finite sample corrected estimate of the variance, which yields a more accurate inference.

4.4 Data description and the link between inequality and redistribution

4.4.1 Data on inequality and computation of redistribution measures

Our main variables of interest are inequality (Ψ) and redistribution (R). To measure inequality, we use the Gini coefficient, which gauges personal income inequality between households within a given country. In principle, the Gini can be calculated using market

[9] Due to the possibility of serially uncorrelated measurement errors in GDP—particularly with regard to the large number of developing countries in our sample—our instrumentation of initial GDP follows the adjustment applied by Bond et al. (2001), who discard $t-1$ differences and $t-2$ levels of per capita GDP from the instrument set.

incomes ("market Gini") or disposable incomes ("net Gini"). Differences in these variables are the result of taxes and transfers. For this reason, our redistribution measure REDIST is calculated as

$$\text{REDIST}_{it} = \text{GINI(M)}_{it} - \text{GINI(N)}_{it} \tag{4.2}$$

where GINI(M) is market inequality, and GINI(N) denotes inequality of disposable incomes. This measure is often referred to as the "pre-post-approach" in the sociological and public policy literature.

When working with cross-national income inequality data, researchers are confronted with a trade-off between the comparability and the coverage of observations (Solt, 2016, 2015). The Luxemburg Income Study (LIS) constitutes the gold standard of cross-nationally comparable inequality data, but the calculation of inequality measures using a uniform set of assumptions and definitions strongly restricts data availability to only 232 observations from 41 countries. The limited scope of countries and years included in the LIS impedes the application of system GMM and does not allow for the investigation of the effect of redistribution based on a large panel of countries. The incorporation of a larger number of observations, however, typically comes at the cost of sacrificing the benefits of comparability and harmonization. Atkinson and Brandolini (2001, 2009) review the pitfalls inherent in the use of secondary datasets and conclude that simple adjustments are not sufficient to generate comparable inequality measures that rest on common income definitions and reference units.

To ease this problem, the Standardized World Income Inequality Database (SWIID) compiled by Solt (2009, 2016) offers model-based multiple imputation estimates of the missing country-years in the LIS series. Next to the benchmark data from the LIS, the SWIID employs source data from a large number of cross-national inequality databases, national statistical offices, and scholarly articles, thereby making use of a maximum of possible information. Hence, the coverage of country-years for which harmonized data is available for both net *and* gross inequality far exceeds those of alternative cross-national inequality datasets. Currently, the SWIID covers 174 countries from 1960 to present with estimates of net income inequality for 4,631 country-years, and estimates of market income inequality for 4,629 country-years. By calculating 5-year averages, we obtain a total of 1,128 country-years, yielding a regression sample of up to 955 observations. As we intend to investigate the effect of inequality and redistribution across different development levels, the large data coverage of the SWIID—particularly with regard to the scope of countries included—is decisive for the purpose of this chapter.

Despite of its large coverage, the SWIID maximizes comparability by closely following the advise from Atkinson and Brandolini (2001, 2009). Essentially, it does so by adopting a flexible missing data algorithm, which produces consistent measures of gross and net inequality, based on information from closely related observations.[10] Thus the SWIID replaces the more or less ad-hoc global fixed adjustments that have long been unavoidable to generate a sufficiently large dataset for cross-country research (as used in, for instance, Forbes, 2000 and Halter et al., 2014).[11] We use version 5.0 of the SWIID, which was published in October 2014. Whereas an earlier version of the dataset was critized by Jenkins (2015), Solt (2015) shows that most of this criticism is misplaced or has been solved with the most recent version of the dataset.

To reflect data uncertainty, the SWIID reports 100 different imputations for every observation, which are generated via Monte Carlo simulations. Thus data uncertainty can be directly incorporated into the regression results via multiple imputation tools, or it can be ignored by averaging the imputations to generate one point estimate for each observation. As Section 4.5.2 shows that multiple imputation estimations hardly affect the estimated coefficients and standard errors, we primarily work with the point estimates.

Our standard redistribution variable REDIST is the difference between market and net Ginis, calculated from all available country-years in the SWIID. While this calculation allows for a large sample of data, caution is advised when interpreting this measure. Some of the Ginis of gross or net income inequality are estimates based on data from neighboring countries, which means that the difference between both measures of inequality contains little information about country specific redistribution. To address this problem, the SWIID reports a sub-sample of most reliable inequality data, for which a measure of redistribution (REDIST(S)) is explicitly provided. This sample is solely based on countries where survey data on net and gross incomes is available. Moreover, as historical data is often less reliable, it neglects observations from developing countries before 1985 and

[10] Appendix A-3 gives a brief summary of the SWIID's standardization process, based on the extensive description in Solt (2016).

[11] For example, it was long common to either ignore the difference between market income inequality and disposable income inequality or to simply assume that both measures differ by a fixed amount, irrespective of the obvious variations in the scope of the welfare state.

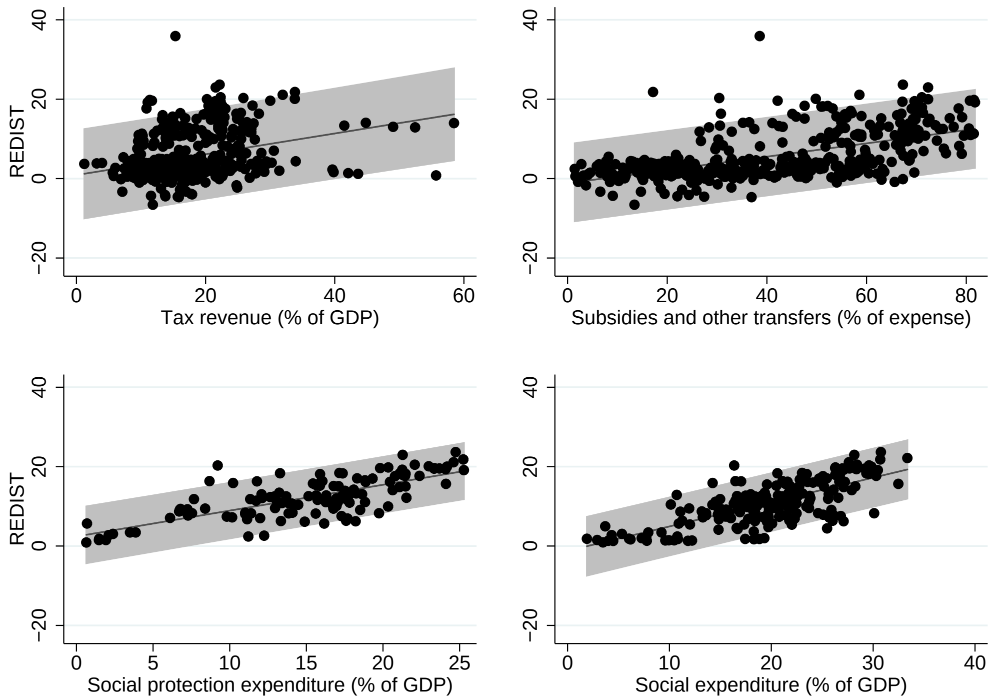


Figure 4.1: Relationship between REDIST and fiscal policy measures
Notes: The figure plots the pre-post redistribution variable REDIST from the SWIID against four proxies of distributive fiscal policy. The data on Tax revenue and Subsidies and other transfers are from the World Bank World Development Indicators. Social protection expenditure and Social expenditure are from the OECD National Accounts Database.

from advanced economies before 1975. Unfortunately, with only 453 country-years (5 year averages), the restricted sample is only half as large as the full sample, which is why we limit the use of the restricted sample to robustness checks and estimations that explicitly focus on the effect of redistribution. Appendix A-4 provides a brief illustration on the extent of redistribution measured by REDIST and REDIST(S) across countries.

The pre-post approach of Equation 4.2 yields a measure of effective redistribution, illustrating the overall result of governmental redistribution via taxes and transfers, rather than the effort by which the result is achieved. Compared to earlier studies, this provides two advantages: First, as their redistributive impact is uncertain and varies considerably across countries, our analysis does not depend on rough redistribution measures such as marginal tax rates or social subsidies. Second, as pre-post redistribution data is (now) more widely available than data on redistributive fiscal policies, our study rests on a considerably expanded number of country-years.

Figure 4.1 plots our measure of effective redistribution against four proxies of governmental redistribution efforts, like social expenditures or tax revenues. It shows that there is a significant correlation between pre-post redistribution and distributive fiscal policy. Foremost, the correlations with social protection expenditure and social expenditure are strong (0.83 and 0.78), suggesting that social spending is often effective in reducing inequality. Somewhat less pronounced is the correlation between redistribution and tax revenues (0.52), which is not surprising, as the volume of tax revenues tells rather little about its usage or the progressiveness of taxation. Altogether, the strong but less than perfect correlations confirm that pre-post redistribution reflects the effect of redistributional policies, but it also suggests that the pre-post data contains additional information not captured by the fiscal policy measures (see, also Ostry et al., 2014).

A potential drawback of the pre-post approach is that market inequality is not independent from the extent of public redistribution (Bergh, 2005). On the lower end of the income scale, a generous welfare system may boost gross inequality by encouraging low income earners to withdraw from the labor market and to live from transfers instead of market income. On the upper end, high income earners may be discouraged by taxes and thus reduce their labor supply, which lowers gross inequality. We follow Ostry et al. (2014) by suggesting that the effect of redistribution on market inequality may not be substantial, as its effects on the lower and on the upper scale of the income distribution are offsetting.

4.4.2 The relationship between inequality and redistribution

The political economy mechanism of the endogenous fiscal policy channel suggests a positive relation between inequality of market incomes and redistribution. Empirical evidence on this channel, however, is rather ambiguous. Whereas earlier studies (e.g. Perotti, 1994, 1996) find a negative relationship between initial inequality and different proxies for redistribution, more recent studies conclude that societies with an unequal distribution of market incomes tend to redistribute more than others (see, e.g., Milanovic, 2000). One explanation for these contradicting results may be the lack of adequate measures for inequality and redistribution. Although the endogenous fiscal policy channel is triggered by the extent of market inequality, some earlier studies use net inequality to explain demand for redistribution. In addition, many studies rely on imperfect measures of redistribution, as the size of public transfers and taxes may be little indication of their redistributive impact.

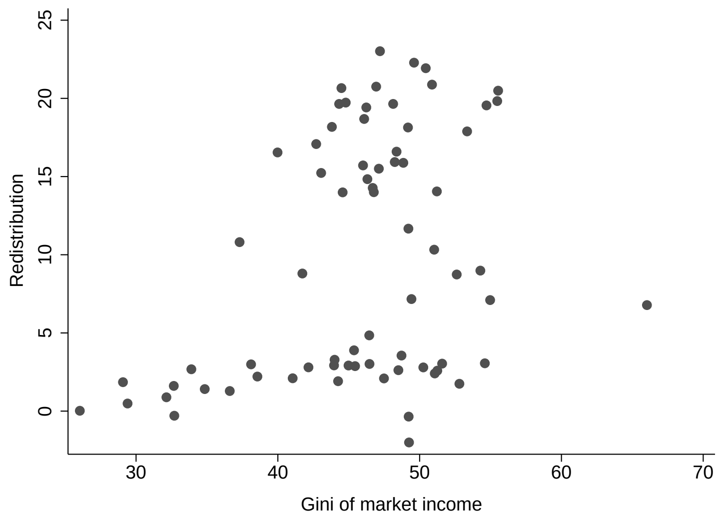


Figure 4.2: Relationship between market inequality and redistribution
Notes: The figure plots observations for each country in the 2005-2009 period. Data is from the restricted sample containing the most reliable data.

Our dataset allows us to reconsider the endogenous fiscal policy channel by using market inequality and effective redistribution based on a large panel of countries. The data implies that lower levels of net inequality are the result of redistributional activities of the government, as the level of redistribution is strongly correlated with the extent of net inequality (correlation: -65 percent).

According to the endogenous fiscal policy channel, we would expect more redistribution in countries that feature a higher level of market inequality. However, a bivariate analysis of the variables in Figure 4.2 reveals only a weak correlation of 21 percent. It turns out that high levels of market inequality in many developing economies are not necessarily accompanied by large redistributional efforts made by the government.[12] Thus the effect of market inequality on redistribution must be examined while holding constant the development level of the economies.

Consider the simple reduced model

$$\text{REDIST(S)}_{it} = \alpha + \delta\text{GINI(M)}_{it} + \beta \log(\text{GDP}_{pc})_{it-1} + \eta_i + \xi_t + \upsilon_{it}$$

where the denotation of the variable is the same as in the previous section. Table 4.1

[12]Observations in the restricted sample REDIST(S) where high levels of market inequality trigger only little redistribution entirely stem from developing economies. These countries include Kenya in 1985 (GINI(M): 57.54, REDIST(S): 5.71), India in 2010 (51.89, 0.53), Honduras in 2010 (54.60, 2.90), Guatemala in 2010 (50.93, 2.69), and South Africa in 2000 (64.75, 4.45). Note that the selection rule of the REDIST(S) sample to exclude observations of developing economies before the year 1985 yields exclusion of the high rates of negative redistribution observed in Guatemala and Kenya during the 1970s.

Table 4.1: The relationship between market inequality and redistribution

	(1) POLS	(2) Within-Group	(3) Within-Group (time-dummies)	(4) Within-Group (2SLS)
GINI(M)	0.249***	0.427***	0.397***	0.401***
	(0.0694)	(0.0588)	(0.0699)	(0.0741)
$\log(\text{GDP}_{pc})$	0.0496***	-0.00106	-0.0199*	-0.000163
	(0.00613)	(0.00646)	(0.0104)	(0.00640)
Constant	-0.473***	-0.0833	0.0842	
	(0.0586)	(0.0628)	(0.101)	
Observations	434	434	434	411
R-squared	0.519	0.473	0.531	0.465

Notes: Table reports regressions of REDIST(S) on GINI(M) using Pooled OLS (Column 1), Within-Group without and with time-dummies (Columns 2 and 3), and 2SLS with country fixed effects (Column 4) estimations. Robust standard errors in parantheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

presents the results of the estimation of the model using Pooled OLS (POLS), Within-Group (WG), and 2SLS estimations. Whereas Column (1) neglects both η_i and ξ_t, Column (2) includes country fixed effects and Column (3) additionally incorporates period fixed-effects. Column (4) conducts 2SLS regressions with fixed-effects, where GINI(M) is instrumented with its lagged values in order to ensure that we are capturing the effect of market inequality on redistribution, rather than the reverse.

The results strongly support the political mechanism of the endogenous fiscal policy channel, as a higher level of market inequality results in a higher amount of redistribution in each of the estimations. Whereas the development level is positively related to the extent of redistribution when using pooled OLS, this influence vanishes after inclusion of country-fixed effects in Columns (2)—(4). One interpretation is that the income level may be a proxy of the deeper institutional causes that distinguish the countries in their level of redistribution. Due to higher transparency, more efficient institutions and less corruption, the opportunities for rent-seeking and crony capitalism decline during the development process. Likewise, less-developed countries tend to be less-democratic. If the voter cannot influence the political process, a higher level of inequality most likely does not yield a higher amount of redistribution.

4.5 Regression results

4.5.1 Baseline regressions

We now turn to the investigation of the growth effect of inequality and redistribution. Table 4.2 reports the results of our baseline system GMM growth estimations when the full sample of available data from the SWIID is used. Our regression sample covers a maximum of 955 observations from 154 countries. The time dimension includes 5-year averages from the initial period 1965-1969 to the period 2010-2012.

Utilizing all available country-year observations, Column (1a) shows a reduced specification of our growth model in which—aside from time dummies and country fixed-effects—the lagged level of per capita income is the only control variable. As mentioned previously, theory suggests that inequality exerts its influence on growth via several transmission channels. These channels involve standard growth determinants such as physical and human capital accumulation, fertility rates, and political stability. Thus, as pointed out by Galor (2009), the only way to identify the full growth effect of income inequality is excluding some of the usual controls.[13] Yet it involves the risk of an omitted variable bias, which is why Section 4.5.4 will show that there is evidence for an effect running from inequality and redistribution towards the suspected transmission variables.

The results in Column (1a) suggest that both high net inequality, but also its cure in the form of public redistribution, are similarly bad for growth. The point estimate of the net Gini is negative and highly significant, suggesting that an increase of the Gini by one standard deviation, i.e. 10 percentage points, lowers the annual growth rate by an average of 2.5 percentage points. The estimated parameter of redistribution is significantly negative as well and roughly the same size as the effect of inequality.

Our sample varies somewhat when we include additional control variables. Thus, Columns (1b)-(4) rest on a sample that contains data for all of the control variables in order to enable a clear comparison between different regression models. The reduction in country-years in the common sample from 955 to 740 is primarily due to a loss of observations on both ends of the time dimensions, which affects both observations from advanced and developing economies. In this smaller sample, both the effect of inequality

[13]By estimation of reduced models, we avoid a potential "bad control" problem (see Angrist and Pischke, 2009).

and redistribution become smaller in size, and the estimated parameter of redistribution becomes insignificant.

In Column (2), the investment share and the average years of school attainment are introduced into the model. Both variables are not only standard components of empirical growth models, but also—according to the theories of differential saving rates, credit-market imperfections, sociopolitical unrest, and endogenous fiscal policy—part of the transmission process from inequality to growth. Holding these transmission variables constant, we would expect this model to show that inequality has a smaller impact on growth. Indeed, the parameter estimate of the Gini declines to -0.099, which is about half of the marginal effect detected in Column (1b). In line with theory and previous empirical studies, the newly introduced controls are positive and significant.

When we introduce a number of additional control variables in Column (3), the effect of inequality shrinks further, but still remains significant. Among the new covariates, only the log of life expectancy—our health variable—is positively related to economic growth, whereas government consumption, inflation, international openness, and political rights are all insignificant.

Some theoretical models suggest that fertility is endogenous to income inequality. Holding the fertility rate constant could thus eliminate another transmission channel. Indeed, in Column (4), the estimated effect of the Gini diminishes and becomes insignificant when fertility is held constant, which resembles the findings by Barro (2000) and De la Croix and Doepke (2003).[14] Similar to their results, the direct effect of fertility is negative and highly significant in our growth regression.

So far, we have focused on inequality but devoted little attention to redistribution. In fact, the estimated coefficient of REDIST in Table 4.2 should be interpreted with caution. Whereas the maximum number of available observations is utilized here, the redistribution variable may be measured imprecisely in certain cases where estimates rest entirely on information from other countries. Hence, Table 4.3 applies REDIST(S), which is calculated from a subsample consisting of only the most reliable observations. The rest of the specifications in each column of Table 4.3 exactly follow the specifications shown in the corresponding columns of Table 4.2. However, our regression sample now shrinks to a maximum of 434 observations from 73 countries.

[14]Our sample composition does not change from Column (3) to Column (4), which strengthens the evidence for the endogenous fertility channel.

Table 4.2: Baseline growth regressions, full sample

	(1a)	(1b)	(2)	(3)	(4)
	Panel A: Instrument matrix with reduced lag-structure				
L.log(GDP$_{pc}$)	0.00117	-0.00255	-0.0110***	-0.0159***	-0.0195***
	(0.00570)	(0.00452)	(0.00372)	(0.00389)	(0.00267)
GINI(N)	-0.248***	-0.195***	-0.0990***	-0.0654***	-0.0283
	(0.0714)	(0.0507)	(0.0331)	(0.0244)	(0.0296)
REDIST	-0.238***	-0.0995	-0.00870	-0.0374	-0.0130
	(0.0789)	(0.0787)	(0.0433)	(0.0439)	(0.0490)
INVS			0.128***	0.0670**	0.0694***
			(0.0332)	(0.0275)	(0.0237)
SCHOOLING			0.00369**	0.00153	0.0000341
			(0.00163)	(0.00144)	(0.00117)
log(LIFEEX)				0.0940***	0.0611***
				(0.0199)	(0.0173)
GOVC				-0.0314	-0.0380
				(0.0262)	(0.0264)
INFL				-0.000316	-0.0000738
				(0.000588)	(0.000529)
OPEN				0.00475	0.00289
				(0.00355)	(0.00356)
POLRIGHT				-0.000199	-0.000626
				(0.00116)	(0.00115)
log(FERT)					-0.0292***
					(0.00786)
Observations	955	740	740	740	740
Countries	154	125	125	125	125
Hansen p-val	0.002	0.019	0.360	0.997	1.000
Diff-Hansen	0.187	0.571	0.854	1.000	1.000
AR(1) p-val	0.000	0.000	0.000	0.000	0.000
AR(2) p-val	0.651	0.355	0.310	0.463	0.609
Instruments	62	62	98	175	192
	Panel B: PCA-version of the instrument matrix				
GINI(N)	-0.255***	-0.210***	-0.0739**	-0.0658**	-0.0219
	(0.0568)	(0.0370)	(0.0346)	(0.0264)	(0.0306)
REDIST	-0.287***	-0.170**	-0.0120	0.0138	0.0102
	(0.0738)	(0.0745)	(0.0449)	(0.0476)	(0.0478)
Observations	955	740	740	740	740
Countries	154	125	125	125	125
Hansen p-val	0.164	0.280	0.692	0.456	0.447
AR(1) p-val	0.000	0.000	0.000	0.000	0.000
AR(2) p-val	0.618	0.306	0.304	0.527	0.652
Instruments	105	105	130	130	130
KM Stat	0.826	0.820	0.885	0.903	0.905
POV explained	1.000	1.000	0.999	0.946	0.940

Notes: Dependent variable is real per capita GDP growth. Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. All regressions include period fixed effects. Hansen p-val gives the J-test for overidentifying restrictions. Diff-Hansen represents the Difference-in-Hansen statistic of the instrument subset for the level equation. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. KM Stat displays the Kaiser-Meyer-Olkin measure of sampling adequacy (see Kaiser, 1974), POV denotes the portion of variance explained by the utilized components. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.3: Baseline growth regressions, restricted sample

	(1a)	(1b)	(2)	(3)	(4)
	Panel A: Instrument matrix with reduced lag-structure				
L.log(GDP$_{pc}$)	-0.00870	-0.00631	-0.0204***	-0.0214***	-0.0257***
	(0.00688)	(0.00843)	(0.00619)	(0.00713)	(0.00770)
GINI(N)	-0.258***	-0.159**	-0.0478	-0.0562	-0.00829
	(0.0739)	(0.0625)	(0.0537)	(0.0383)	(0.0551)
REDIST(S)	-0.229**	-0.132	0.0202	0.0138	0.0268
	(0.0929)	(0.124)	(0.0675)	(0.0569)	(0.0624)
INVS			0.173***	0.165***	0.126***
			(0.0352)	(0.0372)	(0.0454)
SCHOOLING			0.00581**	0.00580**	0.00513**
			(0.00236)	(0.00226)	(0.00242)
log(LIFEEX)				-0.0275	0.0210
				(0.0654)	(0.0541)
GOVC				-0.0846***	-0.0991***
				(0.0279)	(0.0311)
INFL				-0.0000163	-0.000434
				(0.00119)	(0.00115)
OPEN				0.00362	0.00254
				(0.00421)	(0.00411)
POLRIGHT				-0.00189	-0.00226
				(0.00213)	(0.00184)
log(FERT)					-0.0240*
					(0.0132)
Observations	434	374	374	374	374
Countries	73	67	67	67	67
Hansen p-val	0.015	0.010	0.664	1.000	1.000
Diff-Hansen	0.441	0.192	0.993	1.000	1.000
AR(1) p-val	0.000	0.000	0.000	0.000	0.000
AR(2) p-val	0.447	0.204	0.143	0.119	0.146
Instruments	50	50	80	154	169
	Panel B: PCA-version of the instrument matrix				
GINI(N)	-0.240***	-0.175***	-0.0281	-0.0803	0.0339
	(0.0571)	(0.0589)	(0.0534)	(0.0626)	(0.0616)
REDIST(S)	-0.271***	-0.130	0.0674	0.0235	-0.00750
	(0.0856)	(0.104)	(0.0814)	(0.0773)	(0.0727)
Observations	434	374	374	374	374
Countries	73	67	67	67	67
Hansen p-val	0.326	0.514	0.744	0.520	0.434
AR(1) p-val	0.000	0.000	0.000	0.000	0.000
AR(2) p-val	0.305	0.201	0.158	0.155	0.184
Instruments	78	78	78	78	78
KM Stat	0.833	0.834	0.880	0.816	0.825
POV explained	1.000	1.000	0.991	0.914	0.909

Notes: Dependent variable is real per capita GDP growth. Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. All regressions include period fixed effects. Hansen p-val gives the J-test for overidentifying restrictions. Diff-Hansen represents the Difference-in-Hansen statistic of the instrument subset for the level equation. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. KM Stat displays the Kaiser-Meyer-Olkin measure of sampling adequacy (see Kaiser, 1974), POV denotes the portion of variance explained by the utilized components. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Regarding the reduced model of Column (1a), the estimated parameters of redistribution and net inequality are very similar to the results obtained from the full sample estimations. A high level of net inequality is harmful for growth; yet, holding net inequality constant, public redistribution is also negatively related to economic performance. Quantitatively, the results imply that reducing the Gini by ten percentage points lowers economic growth by roughly 2.3 percentage points because of the direct effect of taxes and transfers. On the other hand, growth accelerates by 2.6 percentage points due to the positive effect of the resulting lower level of net inequality.[15] Drawing on the common sample of only 374 observations in Column (1b), the effects of net inequality and redistribution are somewhat smaller than before but still similar in magnitude. In each case, a simple comparison of the estimated parameters of inequality and redistribution suggests that the positive growth effect from a lower level of net inequality is, on average, almost fully offset when the decline in inequality is achieved via taxes and transfers.

The regressions based on the restricted sample illustrate, to an even greater extent than the full sample estimations, how inequality exerts its influence via the transmission channels: when investment and schooling are controlled for in Column (2), the estimated coefficient of inequality shrinks to -0.0478 and loses significance. Meanwhile, the effect of redistribution becomes positive but insignificant. In Column (3), the Gini remains roughly unchanged when additional controls are introduced, all of which are insignificant aside from the negative effect of government consumption. In Column (4)—when the fertility rate is incorporated—the effect of inequality virtually disappears, resembling the corresponding estimation based on the full sample. The main transmission variables of inequality on growth—investment, schooling, and fertility—are significant with the expected sign in all estimations.

Assessing the validity of our results, we refer to the test statistics given in the lower part of Tables 4.2 and 4.3. The first requirement is the absence of second-order serial correlation in the residuals, which does not pose any problem as the AR(2) p-value is always greater than 0.1. In addition, the p-values of Hansen's J-test reported in Columns (2)–(4) of both tables suggest that the null of joint validity of all instruments cannot be rejected; and the Difference-in-Hansen tests emphasize the superiority of system GMM over difference GMM in each model. Yet, with p-values considerably below 0.1, there could be some

[15]The coefficients can be directly compared, as an increase in redistribution by one percentage point lowers net inequality by exactly one percentage point.

doubt about the validity of our instruments in Columns (1a) and (1b). However, since Hansen's J-test is also a general test of structural specification, the rejection of the null in the reduced model may point to an omitted variable problem rather than indicating general invalidity of the instruments (see Roodman, 2009a). As we deliberately omit certain regressors to capture the full impact of inequality and to circumvent potential problems with "bad controls", a rejection of the reduced specification is not surprising.

To avoid an overfitting problem, our set of instruments is restricted to only one lag per variable. Nevertheless, in our extended models reported in Columns (3)–(4), the number of instruments is relatively high because of the large number of presumably endogenous control variables. As a result, the potentially weakened Hansen tests yield high p-values that are close to 1. In light of the inevitable tradeoff between controlling for a large set of covariates and safely avoiding an overfitting problem, we show our full range of model specifications in each of the following sections. As an alternative instrumentation strategy, Panel B of Tables 4.2 and 4.3 reports the results obtained via application of principal component analyses to reduce the instrument count. This strategy further enables us to exploit information stemming from a larger lag structure without the fear of a potentially overfitted specification. Overall, the results in Panel B are strongly comparable to those documented in Panel A. However, the estimated effects tend to be slightly stronger, emphasizing the long-term perspective of the inequality-growth nexus.[16] Regarding the selction of the number of utilized components, the Kaiser-Meyer-Olkin measure points to a high degree of sampling adequacy. In addition, although we only employ a (small) subset of the potentially available components, they account for large parts of the variance in the data. As can be seen in Table 4.12 in the appendix, our main results are also robust to an alternative strategy proposed by Roodman (2009a), avoiding overfitting via a collapsed instrument matrix.

In specifying our instrument matrix, we carefully attended to the concern of weak instruments. Bazzi and Clemens (2013) showed that some of the instrumental variables in widely-cited growth regressions may be weak, casting doubt on the concluded consequences for economic development. Kraay (2015) argues that this problem is particularly severe with respect to empirical investigations on the effect of inequality on growth. Table 4.11 in the appendix follows the suggestion of Bazzi and Clemens (2013) to open

[16] We would like to thank an anonymous referee for suggesting this specification. Full regression results are available from the authors.

the “black box” of GMM by providing two tests proposed by Sanderson and Windmeijer (2016) (henceforth SW). The first is a weak instrument F-test that builds on Angrist and Pischke (2009) but allows for separate diagnostics for each endogenous regressor. The second is the SW χ^2 test for under-identification, which is also reported separately for each regressor. In general, these tests are designed for weak-instrumentation diagnostics of external instruments in IV or 2SLS settings. However, there have been some attempts to transfer these tests to dynamic panel GMM settings (Bun and Windmeijer, 2010; Newey and Windmeijer, 2009) via construction of the exact GMM instrument matrix for both the difference and the levels equation of the system GMM estimator, which can in turn be used to carry-out the standard 2SLS regressions and test.

With respect to our redistribution variable, the SW tests of weak instrumentation show that in each model specification, the relative IV bias is less than 30 percent in both the level and the difference equation, and often even (much) smaller than 10 percent. The test also points to a general instrument strength of our inequality variable, albeit to a slightly lesser extent. The SW χ^2 test shows that underidentification is not a problem in either the levels or the difference equation with respect to both GINI(N) and REDIST. As additional weak instrument diagnostics, we replicate a battery of tests conducted by Kraay (2015), including weak-instrument-robust tests on (joint) significance of the endogenous regressors, as well as weak-instrument-robust confidence intervals. Both the AR-test developed by Anderson and Rubin (1949) and the K-test proposed by Kleibergen (2005) demonstrate the significance of the model specification and our variables of interest.[17]

Weak-instrument-robust confidence intervals are computed based on the conditional likelihood ratio test (CLR) developed by Moreira (2003) and compared with the intervals suggested by the Wald test. The results are not directly comparable to the effects identified in Tables 4.2 and 4.3 as the CLR statistic can only be inverted to obtain weak-instrument-robust confidence intervals in the single-endogenous-regressor case (Finlay and Magnusson, 2009; Finlay et al., 2016), prompting us to re-specify the empirical model so that the remaining variables are treated as exogenous.[18] The computed intervals are robust to weak instruments in the sense that they have the correct size in cases when

[17]In order to obtain test statistics on the significance of GINI(N) and REDIST via the AR-test and the K-test, we use the reduced-model of Column (1a) and assume that the remaining variables are strongly identified.

[18]In the case of multiple endogenous regressors, such inference can only be carried out using projection-based confidence intervals that may be computed by a grid search. These intervals, however, are conservative, meaning that they have asymptotic size less than or equal to nominal size.

instruments are weak as well as when they are not. We focus on Columns (1a) and (1b), where the results suggest a significantly negative effect of both inequality and redistribution. The confidence intervals derived from the CLR test are slightly wider than the Wald confidence intervals, particularly in Column (1a). However, the weak-instrument-robust intervals are entirely in the negative parameter space, suggesting that even in a potential presence of weak instrumentation, the effects of both variables would still be negative.

4.5.2 Sensitivity analysis of the baseline results

The SWIID reports 100 different imputations for every observation in order to reflect the uncertainty that goes in hand with the generation of consistent series of inequality data. As it is common in the literature (see, e.g Ostry et al., 2014 and Acemoglu et al., 2015), we have thus far averaged this data to generate point estimates, which we can handle with regular regression techniques. Yet we can also follow the recommendation of Solt (2016) and directly account for data uncertainty by running multiple imputation regressions. Essentially, the multiple imputation routine estimates repeated regressions for each of the 100 imputations of GINI(N) and REDIST and then pools the results according to the combination rules of Rubin (1987). The estimated standard errors are thus adjusted for the variability between the imputations and hence usually larger than those received by averaged data.[19]

Table 4.4 presents the estimated coefficients of GINI(N) and REDIST resulting from multiple imputation regressions. The reported regression models exactly resemble the baseline system GMM specifications from Table 4.2, except that they are estimated with the full set of imputations instead of the averaged data. Compared to the baseline results, the estimated coefficients do not seem to systemically change in one direction, but the standard errors of GINI(N) and REDIST are slightly larger, leading to slightly less significant effects in Columns (2) and (3). Altogether, however, our baseline results are robust to incorporation of the sampling error of the SWIID imputations, which is why we can safely proceed with the standard system GMM estimator.

As different estimation techniques may yield different implications for the growth effect of inequality (see Neves and Silva, 2014), Table 4.12 in the appendix presents the results

[19]See Brownstone and Valletta (2001) and Jenkins (2015) for a more detailed summary of the multiple imputations technique.

Table 4.4: Baseline growth regressions using multiple imputations estimates

	(1a)	(1b)	(2)	(3)	(4)
	Panel A: Instrument matrix with reduced lag-structure				
$\text{GINI(N)}_{\text{MI}}$	-0.236***	-0.197***	-0.0633*	-0.0425	-0.0179
	(0.0744)	(0.0554)	(0.0337)	(0.0288)	(0.0305)
$\text{REDIST}_{\text{MI}}$	-0.219**	-0.0791	-0.0235	-0.00515	0.00391
	(0.109)	(0.0955)	(0.0569)	(0.0443)	(0.0438)
Observations	955	740	740	740	740
Countries	154	125	125	125	125
MI F Stat	3.664	4.119	9.929	9.970	9.375
MI F p-value	0.000	0.000	0.000	0.000	0.000
Average RVI	0.379	0.243	0.095	0.056	0.045
Largest FMI	0.283	0.216	0.272	0.194	0.199
Imputations	100	100	100	100	100
Instruments	62	62	98	175	192
	Panel B: PCA-version of the instrument matrix				
$\text{GINI(N)}_{\text{MI}}$	-0.240***	-0.207***	-0.0444	-0.0473	-0.0186
	(0.0641)	(0.0476)	(0.0336)	(0.0327)	(0.0343)
$\text{REDIST}_{\text{MI}}$	-0.229***	-0.116	-0.00801	-0.0228	-0.00959
	(0.0875)	(0.0777)	(0.0504)	(0.0498)	(0.0497)
Observations	955	740	740	740	740
Countries	154	125	125	125	125
MI F Stat	5.299	5.468	10.66	7.380	8.521
MI F p-value	0.000	0.000	0.000	0.000	0.000
Average RVI	0.479	0.381	0.082	0.093	0.096
Largest FMI	0.264	0.274	0.286	0.257	0.237
Imputations	100	100	100	100	100
Instruments	105	105	130	130	130

Notes: Dependent variable is real per capita GDP growth. Table reports multiple imputations two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. Control variables and specifications of Panels A and B are identical to the ones applied in the corresponding columns in Table 4.2. All regressions include period fixed effects. MI F Stat gives the F statistic of the multiple imputation estimations, MI F p-value reports the referring p-values. Average RVI documents the average relative variance increase due to nonresponse, largest FMI reports the largest fraction of missing information. Instruments illustrates the number of instruments. Instruments are the second lag of the explanatory variables in levels for the difference equation and the first lag in differences for the level equation. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

from alternative estimation strategies. These techniques include a collapsed version of the instrument matrix (Roodman, 2009a), difference GMM, 3SLS, and optimal systems GMM. The negative effect of inequality and redistribution is visible in each of the reduced specifications.[20] Even more importantly, a change in the lag structure of the instrument matrix does not alter the result.

Finally, we also investigated the growth effect of relative redistribution, i.e. the ratio of REDIST to GINI(M).[21] The results obtained via this strategy are strongly comparable to the outcome based on our measure of absolute redistribution (REDIST).

4.5.3 Overall effects of public redistribution and the endogenous fiscal policy channel

In accordance with the approach of Ostry et al. (2014), our previous regressions examine the effect of redistribution when net inequality is held constant. In this case, the estimated parameter of redistribution captures the intrinsic effect of redistributive taxes and transfers, whereas the effect of net inequality is observed separately. The overall effect of redistribution can then be calculated by summing up the estimated parameters of redistribution and net inequality. Conducting this exercise, the aggregate effect of redistribution turns out to be small; however, its level of significance cannot be evaluated with this technique.

This section is concerned with an alternative approach that allows us to assess whether the aggregate effect of redistribution is statistically significant. Below, we directly estimate the aggregate growth effect of public redistribution in the restricted sample of high quality data. Leaving net inequality open, the estimated parameter of redistribution captures both the *direct* incentive effect of redistributive taxes and transfers plus the *indirect* effect

[20] First-difference GMM yields some indication for a positive effect of redistribution on growth. However, this technique results in a decline of the number of observations from 740 to 602. The reason is that the estimator requires having at least three consecutive observations for each of the regressors, thereby magnifying gaps in our sample. In addition, the Difference-in-Hanson statistics reported in Table 4.2 emphasize that the extra moment conditions of system GMM are valid, resulting in substantial efficiency losses when using first-difference GMM. Contrary to some earlier studies that rely on time-series variation (e.g. Li and Zou, 1998 and Forbes, 2000), our first-difference GMM estimates support the negative effect of net inequality on growth found in our baseline estimates. The reason for the deviation is twofold. First, earlier studies are based on a substantially lower number of countries. As we might expect the negative effect of net inequality to be more pronounced in poor countries, the neglect of data from the developing world yields a bias in the estimation. Second, previous studies on the topic largely ignore the incomparability problems that arise when using different data compilations, which is heavily criticized by Solt (2016).

[21] The outcomes can be obtained upon request.

Table 4.5: Overall growth effects of redistribution, restricted sample

	(1a)	(1b)	(2)	(3)	(4)
	Panel A: Instrument matrix with reduced lag-structure				
GINI(M)	-0.259***	-0.173**	-0.0412	-0.0511	-0.00193
	(0.0674)	(0.0676)	(0.0502)	(0.0405)	(0.0541)
REDIST(S)	0.0649	0.0845	0.104	0.0822	0.0234
	(0.107)	(0.131)	(0.0912)	(0.0689)	(0.0717)
Observations	434	374	374	374	374
Countries	73	67	67	67	67
Hansen p-val	0.018	0.016	0.668	1.000	1.000
Diff-Hansen	0.550	0.367	0.995	1.000	1.000
AR(1) p-val	0.000	0.000	0.000	0.000	0.000
AR(2) p-val	0.518	0.217	0.135	0.112	0.135
Instruments	50	50	80	154	169
	Panel B: PCA-version of the instrument matrix				
GINI(M)	-0.240***	-0.147***	-0.0517	-0.0541	0.0598
	(0.0591)	(0.0534)	(0.0440)	(0.0689)	(0.0464)
REDIST(S)	-0.000451	0.0396	0.0938	0.0356	-0.0166
	(0.0914)	(0.104)	(0.0811)	(0.0894)	(0.0718)
Observations	434	374	374	374	374
Countries	73	67	67	67	67
Hansen p-val	0.117	0.139	0.411	0.128	0.226
AR(1) p-val	0.000	0.000	0.000	0.000	0.000
AR(2) p-val	0.403	0.244	0.149	0.152	0.165
Instruments	68	68	68	68	68
KM Stat	0.818	0.823	0.874	0.788	0.820
POV explained	0.999	0.999	0.981	0.896	0.891

Notes: Dependent variable is real per capita GDP growth. Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. All regressions include period fixed effects. Hansen p-val gives the J-test for overidentifying restrictions. Diff-Hansen represents the Difference-in-Hansen statistic of the instrument subset for the level equation. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. KM Stat displays the Kaiser-Meyer-Olkin measure of sampling adequacy (see Kaiser, 1974), POV denotes the portion of variance explained by the utilized components. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

resulting from the change in net inequality. The Gini of market inequality, GINI(M), which is possibly affected by some feedback effects of redistribution, is kept constant in this case. In other words, we examine the overall effect of redistribution for a given level of market inequality in Table 4.5. Aside from the application of a different measure of inequality, the rest of the specifications exactly follow the corresponding columns in Table 4.3. As there are virtually no changes in the effects of the covariates, we only report the variables of interest.

Holding market inequality constant, the coefficient of redistribution is positive in each regression model.[22] Obviously the negative direct growth effect of redistribution and the indirect positive effect achieved via a lower level of net inequality are offsetting.[23]

What do our results imply about the validity of the endogenous fiscal policy channel? Whereas Section 4.4.2 provides evidence for the political economy mechanism, the results in Table 4.5 at first glance seem to contradict the economic mechanism. However, such a conclusion would be premature as the exploration of the economic mechanism requires disentanglement of the causes of an equal distribution of incomes. There are two reasons why net inequality may be low: either because of government redistribution or because of a low level of market inequality. Our results from Section 4.5.1 indicate that societies with an equable distribution of net *and* market incomes experience higher growth rates compared to societies where a low level of net inequality is the result of public redistribution. This finding highlights negative incentive effects of redistribution, which is in line with the economic mechanism of the fiscal policy channel.

4.5.4 Empirical investigation of the transmission channels

In the previous regressions the effect of inequality and redistribution diminishes when we control for investment, schooling, and fertility. Table 4.6 illustrates how the separate introduction of each of the suspected transmission variables affects the estimated coefficients of inequality and redistribution. To avoid that different sample compositions yield changes in the point estimates, all estimations are based on a common regression sample. Whereas inequality and redistribution exert sizable negative effects in the reduced model, the effect of inequality vanishes after controlling for school attainment or the fertility rate. In contrast, the introduction of the investment share primarily shrinks the coefficient of redistribution but leaves inequality rather unaffected.

Altogether, these results could pose evidence that inequality and redistribution exert their influence on growth via transmission channels acting specifically through these variables. Holding constant the transmission variables would thus shut down the trans-

[22] Surprisingly, market inequality is negatively correlated to economic growth in Column (1), although theory suggests that it is the distribution of *disposable* incomes that affects growth. Hence, the estimated coefficient of market inequality seems to capture the growth effect of net inequality, which vanishes when its transmission variables are held constant. In fact, even though redistributive policies differ across countries, they only slightly affect inequality rankings.

[23] Regression models that include redistribution but do not control for any measure of inequality yield a similarly negligible effect. Results are available upon request.

mission channels of inequality, which means that a reduced model would be preferable. Yet the causality is unclear. Whereas the theories of Section 4.2 predict a causal effect of inequality and redistribution, a reverse causation is plausible as well.

Table 4.6: Growth effects when transmission variables are held constant

	(1)	(2)	(3)	(4)	(5)
	Panel A: Instrument matrix with reduced lag-structure				
L.log(GDP_{pc})	-0.00407	-0.00482	-0.0119**	-0.0114***	-0.0202***
	(0.00698)	(0.00500)	(0.00489)	(0.00429)	(0.00542)
GINI(N)	-0.180**	-0.0865	-0.116***	0.0324	0.0170
	(0.0771)	(0.0599)	(0.0409)	(0.0860)	(0.0471)
REDIST(S)	-0.196*	-0.157*	-0.0883	-0.0719	0.000536
	(0.111)	(0.0931)	(0.0609)	(0.102)	(0.0766)
SCHOOLING		0.00360*			0.00301**
		(0.00193)			(0.00130)
INVS			0.146***		0.149***
			(0.0346)		(0.0393)
log(FERT)				-0.0548***	-0.0298***
				(0.00918)	(0.00847)
Observations	410	410	410	410	410
Countries	67	67	67	67	67
Diff-Hansen	0.339	0.626	0.772	0.925	1.000
Hansen p-val	0.012	0.080	0.128	0.164	0.948
AR(1) p-val	0.000	0.000	0.000	0.000	0.000
AR(2) p-val	0.526	0.522	0.350	0.642	0.540
Instruments	50	65	65	65	95
	Panel B: PCA-version of the instrument matrix				
GINI(N)	-0.153**	-0.0830	-0.130**	0.0261	0.0247
	(0.0599)	(0.0556)	(0.0521)	(0.0687)	(0.0533)
REDIST(S)	-0.203**	-0.126	-0.121**	-0.0319	-0.0290
	(0.0970)	(0.101)	(0.0565)	(0.0818)	(0.0786)
Observations	410	410	410	410	410
Countries	67	67	67	67	67
Hansen p-val	0.521	0.449	0.387	0.688	0.551
AR(1) p-val	0.000	0.000	0.000	0.000	0.000
AR(2) p-val	0.393	0.513	0.330	0.700	0.569
Instruments	78	78	78	78	78
KM Stat	0.833	0.862	0.865	0.859	0.886
POV explained	1.000	0.998	0.997	0.998	0.979

Notes: Dependent variable is real per capita GDP growth. Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. All regressions include period fixed effects. Hansen p-val gives the J-test for overidentifying restrictions. Diff-Hansen represents the Difference-in-Hansen statistic of the instrument subset for the level equation. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. KM Stat displays the Kaiser-Meyer-Olkin measure of sampling adequacy (see Kaiser, 1974), POV denotes the portion of variance explained by the utilized components. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

To counter this problem, Table 4.7 directly examines how inequality and redistribution affect the suspected transmission variables. Each of the major transmission variables, investment, schooling and fertility, is regressed on the reduced empirical specification that we employed in the previous sections to explain economic growth. This approach provides the advantage of good comparability among the transmission regressions and our main growth regressions.[24] Moreover, the lag instrumentation of the system GMM estimator allows us to get a tentative impression about the direction of causality. All regressions are based on a common sample of 395 country-years to maximize comparability of the results between the different model specifications.

The first column of Table 4.7 reports an estimation of the investment share, which is insignificantly related to the Gini of net incomes but negatively affected by redistribution. Since the positive investment effect of differential saving rates counteracts the negative impact of capital market imperfections or sociopolitical unrest, the undetermined effect of inequality is consistent with the theoretical ambiguity. In contrast, the incentive effects of redistribution seem to matter for investment decisions, which is not surprising as progressive taxes lower the return on investment.

The results from the schooling and fertility regressions in Columns (2) and (3) directly confirm our expectations from theory and the reduced-form estimates. Whereas inequality has a positive effect on the fertility rate, it negatively affects school attainment. Redistribution is insignificantly related to schooling, but significantly increases fertility.

From theory it follows that credit constraints might reinforce the impact of inequality on its transmission variables. Empirically, such a conditional effect can be examined by the introduction of an interaction term into the model. Ideally, we would want to introduce an interaction term between the Gini and a moderator variable that directly measures the degree of imperfections in capital markets. As such a variable does not exist, the ratio of private credit to GDP (CREDIT) serves as a proxy for credit availability.[25]

Indeed, the results from Columns (4)—(6) reveal that the net Gini and its interaction term with CREDIT are individually and jointly significant in both the schooling and the fertility regression, but insignificant in the investment regression.[26] The estimated

[24] Although system GMM is designed for dynamic models, it does not require the dependent variable to appear on the right hand side (see Roodman, 2009b).

[25] We instrument the credit ratio and the interaction term with their lagged values, as they are possibly endogenous to growth. The data source of CREDIT is World Bank (2014).

[26] See the p-values on the Wald tests of joint significance, given in the last line of Table 4.7.

Table 4.7: Transmission channels of inequality, restricted sample

	(1) INVS	(2) SCHOOLING	(3) FERT	(4) INVS	(5) SCHOOLING	(6) FERT
	Panel A: Instrument matrix with reduced lag-structure					
log(GDP$_{pc}$)	0.103***	0.0766	-0.500**	0.0814***	0.613	-0.598***
	(0.0176)	(0.297)	(0.199)	(0.0157)	(0.438)	(0.171)
GINI(N)	-0.211	-11.70***	7.334***	-0.260	-15.43***	10.21***
	(0.262)	(4.109)	(2.741)	(0.232)	(4.779)	(2.280)
REDIST(S)	-1.100***	2.569	7.363**	-0.935***	-1.135	5.615***
	(0.380)	(4.873)	(2.861)	(0.283)	(4.333)	(2.015)
CREDIT				-0.0504	-2.556***	2.483***
				(0.0665)	(0.969)	(0.509)
GINI×CREDIT				0.252	5.764*	-6.523***
				(0.200)	(3.211)	(1.439)
Observations	395	395	395	395	395	395
Countries	67	67	67	67	67	67
Hansen p-val	0.230	0.074	0.065	0.642	0.661	0.665
Diff-Hansen	0.985	0.321	0.822	1.000	0.906	0.991
AR(1) p-val	0.153	0.013	0.014	0.165	0.051	0.008
AR(2) p-val	0.032	0.278	0.380	0.069	0.905	0.118
Instruments	50	50	50	80	80	80
Joint p-val				0.443	0.004	0.000
	Panel B: PCA-version of the instrument matrix					
log(GDP$_{pc}$)	0.113***	0.117	-0.553***	0.0843***	0.629*	-0.618***
	(0.0199)	(0.297)	(0.206)	(0.0178)	(0.333)	(0.148)
GINI(N)	-0.0391	-12.48**	7.447***	-0.327	-13.19***	9.774***
	(0.257)	(5.204)	(2.213)	(0.245)	(4.168)	(2.687)
REDIST(S)	-1.068***	1.485	7.480***	-0.960***	0.498	6.357***
	(0.340)	(4.789)	(2.702)	(0.230)	(3.794)	(1.848)
CREDIT				-0.0810	-2.646***	2.224***
				(0.108)	(1.011)	(0.622)
GINI×CREDIT				0.355	6.129**	-5.909***
				(0.313)	(2.887)	(1.837)
Observations	395	395	395	395	395	395
Countries	67	67	67	67	67	67
Hansen p-val	0.497	0.542	0.479	0.514	0.822	0.725
AR(1) p-val	0.097	0.016	0.014	0.154	0.040	0.006
AR(2) p-val	0.032	0.253	0.334	0.0748	0.865	0.152
Instruments	78	78	78	78	78	78
KM Stat	0.830	0.830	0.830	0.763	0.763	0.763
POV explained	1.000	1.000	1.000	0.990	0.990	0.990
Joint p-val				0.377	0.007	0.001

Notes: Dependent variables are investment shares (INVS), fertility (FERT), and schooling (SCHOOLING). Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. All regressions include period fixed effects. Hansen p-val gives the J-test for overidentifying restrictions. Diff-Hansen represents the Difference-in-Hansen statistic of the instrument subset for the level equation. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. KM Stat displays the Kaiser-Meyer-Olkin measure of sampling adequacy (see Kaiser, 1974), POV denotes the portion of variance explained by the utilized components. Joint p-val shows the p-values on the Wald test for joint significance of GINI(N) and its product with the respective moderator variable. Joint p-val shows the p-values of the Wald test for joint significance of GINI(N) and its product with CREDIT for all interaction models. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

parameters imply that the negative effect of inequality on schooling as well as the positive effect of inequality on fertility are stronger the lower the availability of credit. Poor families seem to choose a higher quantity of children if they are unable to finance their children's education because of credit market restrictions. Hence, the data supports the endogenous fertility and the credit market imperfection channel.

In Table 4.8 we test whether a conditional relationship between inequality and the transmission variables also applies to the effect of inequality on growth. Therefore, we introduce the interaction term between inequality and credit availability in the baseline models of Table 4.2. In the reduced model reported in Column (1), both the Gini and the interaction term with the credit to GDP ratio are highly significant, individually and jointly. Based on the results from this regression, the solid upwards-sloping line in Figure 4.3 plots the marginal growth effect of inequality across different levels of CREDIT.[27] As indicated by the dashed 90 percent confidence bands, the marginal effect of inequality is negative at low values of CREDIT, but becomes insignificant at a credit to GDP ratio of roughly 60 percent, which is located around the 75th percentile of our sample. However, only at very high levels of CREDIT the effect of inequality turns significantly positive. The critical value lies at a credit to GDP ratio of about 130 percent, which is located above the 90th percentile of the sample.

Our regressions of the transmission variables suggest that much of the negative influence of inequality on growth results from forgone investments in human capital. In addition, some of the most productive investment opportunities (in regard to human or physical capital) may be replaced by less productive alternatives. Yet we can only control for the quantity of investments, and not for their average productivity. This might be one reason why the interaction effect shrinks, but still remains significant when we control for the investment share and the average years of schooling in Columns (2) and (3). Similarly to the baseline regressions, inequality and its product with the credit to GDP ratio only become insignificant when the fertility rate is introduced in Column (4). By holding fertility constant, we eliminate another element of the credit market imperfections channel. As a result and in line with our previous findings, the growth effect of inequality vanishes.

[27]The figures illustrating interaction effects with continuous modifying variables are based on the algorithm suggested by Brambor et al. (2006).

Table 4.8: Conditional effects of inequality on growth

	Moderator I: Level of financial development				*Moderator II: Public spending on education*	
	(1)	(2)	(3)	(4)	(1)	(2)
	Panel A: Instrument matrix with reduced lag-structure					
L.log(GDP$_{pc}$)	-0.00138	-0.00619*	-0.0131***	-0.0150***	0.00363	-0.00742**
	(0.00502)	(0.00370)	(0.00320)	(0.00365)	(0.00512)	(0.00362)
GINI(N)	-0.272***	-0.140***	-0.0805***	-0.0240	-0.240***	-0.113**
	(0.0696)	(0.0449)	(0.0290)	(0.0406)	(0.0650)	(0.0567)
MODERATOR	-0.112***	-0.0836***	-0.0555***	-0.0296**	-1.605***	-0.822*
	(0.0301)	(0.0210)	(0.0144)	(0.0150)	(0.597)	(0.484)
GINI×MODERATOR	0.293***	0.179***	0.113***	0.0511	2.734**	1.288
	(0.0920)	(0.0563)	(0.0376)	(0.0420)	(1.143)	(1.009)
REDIST	-0.0181	0.0810	0.0469	0.0156	-0.153**	-0.113**
	(0.0606)	(0.0543)	(0.0489)	(0.0520)	(0.0669)	(0.0544)
INVS		0.137***	0.0843***	0.0769***		0.0906***
		(0.0261)	(0.0225)	(0.0230)		(0.0243)
SCHOOLING		0.00233	0.000992	-0.000285		0.00595***
		(0.00151)	(0.00120)	(0.000991)		(0.00167)
log(LIFEEX)			0.0996***	0.0662***		
			(0.0199)	(0.0188)		
GOVC			-0.0276	-0.0292		
			(0.0237)	(0.0236)		
INFL			-0.000902	-0.000717		
			(0.000721)	(0.000648)		
OPEN			0.00270	0.00279		
			(0.00298)	(0.00315)		
POLRIGHT			-0.00120	-0.00148		
			(0.00127)	(0.00131)		
log(FERT)				-0.0279***		
				(0.00812)		
Observations	713	713	713	713	665	665
Countries	123	123	123	123	122	122
Hansen p-val	0.156	0.709	1.000	1.000	0.195	0.434
Diff-Hansen	0.956	1.000	1.000	1.000	0.834	0.924
AR(1) p-val	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) p-val	0.344	0.285	0.447	0.656	0.522	0.639
Instruments	98	134	209	226	87	121
Joint p-val	0.000	0.003	0.006	0.438	0.110	0.001
	Panel B: PCA-version of the instrument matrix					
GINI(N)	-0.270***	-0.110**	-0.0458	0.0144	-0.283***	-0.199***
	(0.0541)	(0.0444)	(0.0389)	(0.0374)	(0.0712)	(0.0585)
MODERATOR	-0.101***	-0.0657***	-0.0294	-0.0131	-1.493***	-1.608***
	(0.0244)	(0.0183)	(0.0207)	(0.0201)	(0.544)	(0.517)
GINI×MODERATOR	0.266***	0.126**	0.0342	-0.00361	2.734**	2.973***
	(0.0733)	(0.0491)	(0.0614)	(0.0577)	(1.087)	(1.048)
Observations	713	713	713	713	665	665
Countries	123	123	123	123	122	122
Hansen p-val	0.690	0.867	0.722	0.755	0.816	0.738
AR(1) p-val	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) p-val	0.376	0.281	0.492	0.611	0.526	0.577
Instruments	140	140	140	140	140	140
KM Stat	0.806	0.857	0.870	0.873	0.844	0.881
POV explained	0.999	0.992	0.942	0.937	1.000	0.994
Joint p-val	0.000	0.024	0.474	0.898	0.000	0.003

Notes: Dependent variable is real per capita GDP growth. Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. All regressions include time dummies. Hansen p-val gives the J-test for overidentifying restrictions. Diff-Hansen represents the Difference-in-Hansen statistic of the instrument subset for the level equation. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. KM Stat displays the Kaiser-Meyer-Olkin measure of sampling adequacy (see Kaiser, 1974), POV denotes the portion of variance explained by the utilized components. Joint p-val shows the p-values on the Wald test for joint significance of GINI(N) and its product with the respective moderator variable. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

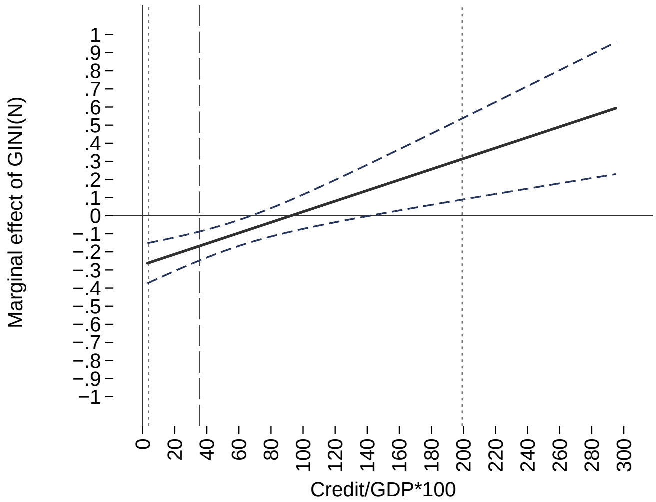


Figure 4.3: Marginal effect of inequality on growth at different levels of credit availability
Notes: Values are calculated using the results of the growth regression in Column (1) of Table 4.8. The upwards sloping line plots the marginal effect of inequality across different levels of the credit to GDP ratio. Surrounding dashed lines represent the 90% confidence intervals. Vertical lines indicate the distribution of the credit to GDP ratio in the sample: dotted lines mark the first and 99th percentiles, the dashed line marks the median value.

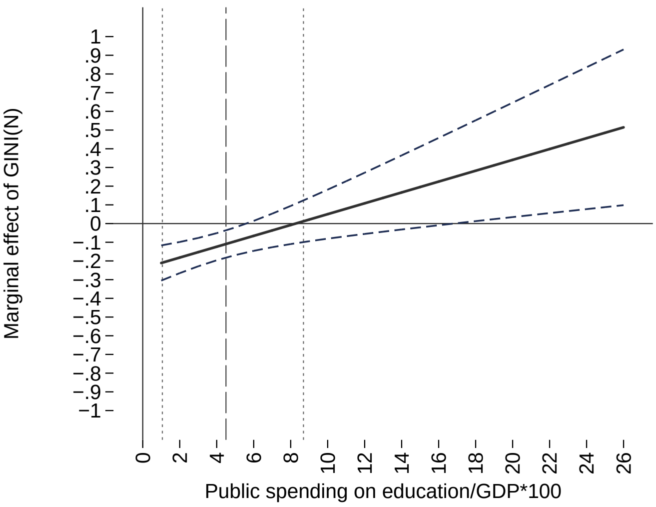


Figure 4.4: Marginal effect of inequality on growth at different levels of public spending on education
Notes: Values are calculated using the results of the growth regression in Column (5) of Table 4.8. The upwards sloping line plots the marginal effect of inequality across different levels of Public spending on education/GDP. Surrounding dashed lines represent the 90% confidence intervals. Vertical lines indicate the distribution of public spending on education/GDP in the sample: dotted lines mark the first and 99th percentiles, the dashed line marks the median value.

Finally, the effect of inequality on growth is subject to another conditionality: a dissipation of intellectual potential occurs if inequality is high and education is expensive for poorer households. Thus the growth effect of inequality could depend on the volume of public spending on education, which could ease the access to education for the poor. Indeed, the negative marginal effect of inequality on growth seems to be stronger if public education spending is low. Figure 4.4 plots the marginal effect of inequality based on a regression model that includes an interaction term between the net Gini and the ratio of public education spending to GDP (PSEDUC).[28] When education spending increases, the negative effect of inequality diminishes, becoming insignificant once a level of roughly 6 percent is passed.

In summary, this section shows that inequality exerts its influence on growth by reducing the average level of human capital and increasing the fertility rate, particularly in countries where credit availability is low. Physical capital investments, however, are relatively unaffected by inequality, but reduced by public redistribution via taxes and transfers. In addition, redistribution raises the fertility rate. Finally, a highly developed public education system seems to mitigate the negative effect of inequality on growth.

4.5.5 Different development levels

The basic regression results suggest that inequality and growth are negatively related. However, this conclusion is based on the whole sample, whereas we suspect that the effect of inequality on growth varies across different development levels (see Barro, 2000, Galor and Moav, 2004, and Castelló-Climent, 2010).

Figure 4.5 illustrates the marginal growth effect of the Gini coefficient for different development levels and the associated 90 percent confidence interval. The underlying model is Column (1a) of Table 4.9, where we introduce an interaction term between the Gini coefficient and initial incomes, denoted by GINI$\times$L.log(GDP$_{pc}$). This inclusion allows for investigation of the impact of inequality without relying on fixed threshold values to distinguish between development levels. We conduct the analysis identically to the baseline specification; however, for reasons of lucidity, Table 4.9 only reports the interacting variables, as there are virtually no changes in the effects of the covariates.

[28]The data source of PSEDUC is World Bank (2014).

Table 4.9: Impact of inequality across different levels of development, estimated via interaction terms

	(1a)	(1b)	(2)	(3)	(4)
	Panel A: Instrument matrix with reduced lag-structure				
L.log(GDP$_{pc}$)	-0.0557**	-0.0542**	-0.0513***	-0.0393***	-0.0355***
	(0.0254)	(0.0243)	(0.0174)	(0.0120)	(0.0113)
GINI(N)	-1.409***	-1.251**	-0.918**	-0.545**	-0.359
	(0.522)	(0.521)	(0.368)	(0.228)	(0.235)
GINI×L.log(GDP$_{pc}$)	0.145**	0.129**	0.0976**	0.0574**	0.0405
	(0.0630)	(0.0625)	(0.0435)	(0.0274)	(0.0274)
Observations	955	740	740	740	740
Countries	154	125	125	125	125
Hansen p-val	0.008	0.005	0.353	1.000	1.000
Diff-Hansen	0.677	0.423	0.962	1.000	1.000
AR(1) p-val	0.000	0.000	0.000	0.000	0.000
AR(2) p-val	0.455	0.242	0.214	0.382	0.524
Instruments	78	78	114	191	208
Joint p-val	0.000	0.000	0.000	0.002	0.286
	Panel B: PCA-version of the instrument matrix				
L.log(GDP$_{pc}$)	-0.0540**	-0.0471**	-0.0557***	-0.0325**	-0.0300**
	(0.0241)	(0.0222)	(0.0138)	(0.0154)	(0.0129)
GINI(N)	-1.387***	-1.128**	-1.000***	-0.347	-0.210
	(0.482)	(0.454)	(0.297)	(0.302)	(0.275)
GINI×L.log(GDP$_{pc}$)	0.141**	0.115**	0.110***	0.0337	0.0229
	(0.0569)	(0.0554)	(0.0359)	(0.0364)	(0.0327)
Observations	955	740	740	740	740
Countries	154	125	125	125	125
Hansen p-val	0.144	0.448	0.746	0.423	0.452
AR(1) p-val	0.000	0.000	0.000	0.000	0.000
AR(2) p-val	0.434	0.232	0.188	0.464	0.639
Instruments	130	130	130	130	130
KM Stat	0.750	0.747	0.849	0.893	0.893
POV explained	1.000	1.000	0.997	0.945	0.938
Joint p-val	0.000	0.000	0.000	0.023	0.664

Notes: Dependent variable is real per capita GDP growth. Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. Covariates are identical to Table 4.2. All regressions include period fixed effects. Hansen p-val represents the J-test for overidentifying restrictions. Diff-Hansen gives the Difference-in-Hansen statistic of the instrument subset for the level equation. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. KM Stat displays the Kaiser-Meyer-Olkin measure of sampling adequacy (see Kaiser, 1974), POV denotes the portion of variance explained by the utilized components. Joint p-val shows the p-values on the Wald test for joint significance of GINI(N) and its product with the respective moderator variable. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

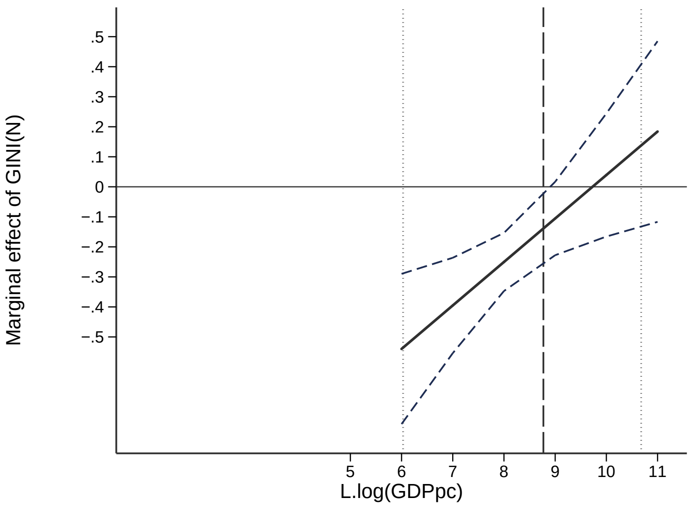


Figure 4.5: Marginal effect of inequality on growth at different development levels
Notes: Values are calculated using the results of the growth regression in Column (1a) of Table 4.9. The upwards sloping line plots the marginal effect of inequality at various levels of development. Surrounding dashed lines represent the 90% confidence intervals. Vertical lines indicate the distribution of the development level in the sample: dotted lines mark the first and 99th percentiles, the dashed line marks the median value.

It turns out that the marginal effect of net inequality on growth is significantly negative in poor economies. Yet the impact of an unequal distribution of incomes weakens as the economies develop and eventually turns insignificant. The null is reached at an income level of roughly 16,500 USD, but the effect of inequality already ceases to be significant once an average threshold of approximately 8,000 USD is exceeded. In economies with incomes larger than 16,500 USD, the effect of inequality tends to become positive, but the confidence interval indicates that this influence is far from significant.

Figure 4.6 illustrates the results from a similar analysis concerning the influence of redistribution across different levels of development by inclusion of REDIST$\times$L.log(GDP$_{pc}$).[29] The figure highlights that redistribution contributes positively to economic growth in earlier stages of development. However, once the economies reach an average income level of again approximately 16,500 USD, the effect on growth tends to be negative.

Our findings emphasize the need to distinguish between the development level when aiming to evaluate the effect of redistributive policies. In poor countries, opportunities for investments in human capital are unequally distributed among households. In the presence of underdeveloped financial markets, weak public education systems, and high

[29]The results of these estimations are reported in Table 4.13 in the appendix.

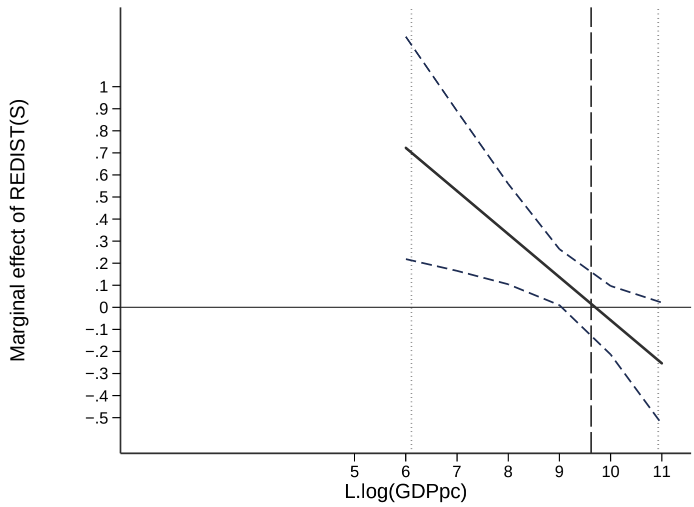


Figure 4.6: Marginal effect of redistribution on growth at different development levels
Notes: Values are calculated using the results of the growth regression in Column (1a) of Table 4.13 in the appendix. The upwards sloping line plots the marginal effect of redistribution at various levels of development. Surrounding dashed lines represent the 90% confidence intervals. Vertical lines indicate the distribution of the development level in the sample: dotted lines mark the first and 99th percentiles, the dashed line marks the median value.

opportunity costs for education, budget constraints are binding and the initial wealth endowment of the family determines the education level of the children. In this case, redistribution as a policy measure to increase equality of opportunities exerts positive effects on growth. The development process of the economies is typically accompanied by a substantial expansion of the financial system and improvements in public education systems. All of these effects lead to a decline in the influence of inequality by improving families' prospects of achieving a higher education level for their children. Once the distribution of human capital endowment is due much more to preferences and individual skills rather than to initial wealth, high education rents may even lead to a growth-enhancing effect of inequality. In this case, redistribution may increasingly act as an impediment to growth.

4.6 Conclusion

Based on a current set of harmonized worldwide data, this chapter finds that income inequality has a robust negative effect on growth when the transmission variables of inequality are left open. By showing that less equal societies tend to have a less educated population and higher fertility rates, in particular when credit availability is low, the chapter supports the credit market imperfections and the endogenous fertility channel. In contrast, the correlation between inequality and physical capital investment is rather weak.

In line with the political economy mechanism of the endogenous fiscal policy channel, a higher level of market inequality predicts more public redistribution. Moreover, redistribution by taxes and transfers seems to directly harm economic growth when net inequality is held constant. We find evidence that this may be due to an impairment of physical capital investment and an increase in the fertility rate.

When estimating the aggregate growth effect of redistribution—its direct negative effect combined with its indirect positive effect resulting from lower net inequality—our results suggest that both effects are offsetting. Thus, at a given level of market inequality, redistribution seems to be a free lunch. Nonetheless, the most growth friendly environment is a low level of net inequality that stems from an equable distribution of market incomes, but not from redistributive taxes and transfers.

Finally, this chapter shows that the growth effects of inequality and redistribution vary with the development level. A negative impact of inequality prevails in developing and middle-income countries, where the negative potential for inequality is severe due to capital market imperfections and an insufficient provision of public goods. In high income countries, where opportunities are on average distributed more equally, no significant correlation between inequality and growth occurs. Likewise, the chapter reveals that redistribution by taxes and transfers is beneficial for growth in poor countries, but rather harmful in rich economies.

A relatively new branch of the literature decomposes overall inequality into several categories, particularly distinguishing between inequality of opportunity (IO) and inequality of effort or outcomes (Marrero and Rodriguez, 2013; Roemer and Trannoy, 2016; Marrero et al., 2016). This literature argues that IO is harmful to growth, while inequality of effort may be growth-enhancing due to incentive effects. Our results provide further evidence in this direction by identifying a strong negative effect of inequality in lower-developed nations with a higher average IO, whereas this effect vanishes in affluent countries where inequality of effort is (much) more prevalent (see Ferreira and Gignoux, 2011; Roemer and Trannoy, 2016). Our analysis also implies that public spending on education as well as financial development may mitigate the negative growth-impulses of IO.

Two paths for future research remain: First, it is still possible that a low level of education and a high fertility rate are the *cause* rather than the *effect* of inequality. Although we estimate an empirical relationship running from inequality to education and fertility, more research is necessary in order to fully rule out that results are driven by feedback effects. Second, as the pre-post approach measures effective redistribution, it does not provide insights on the growth effects of specific redistributive policies. Future research should identify and analyze the policy instruments by which redistribution is achieved, and, in doing so, determine how it can be accomplished most efficiently.

4.7 Appendix to chapter 4

Appendix A-1: Data sources and descriptive statistics of the variables used in the regressions

The growth rate of real per capita GDP as well as the initial level of GDP, the investment share (INVS), the degree of openness (OPEN), and government consumption (GOVC) are from PWT 8.0 as published by Feenstra et al. (2015). The average years of schooling (SCHOOLING) is from Barro and Lee (2013) and includes the years of primary, secondary, and tertiary education that individuals of age 25 and older have received during their educational training. POLRIGHT denotes an index of democracy and rule of law d with $d \in (1, 7)$, provided by Freedom House (2014). As the variable is coded inversely—i.e. lower numbers are associated with higher rates of democracy—we recode the variable to obtain POLRIGHT $= 8 - d$ to make sure that the coefficient in the estimation illustrates the impact of an increase in democracy, rather than the reverse. We further use fertility rates (FERT), inflation rates (INFL) and data on life expectancy at birth (LIFEEX) as reported by World Bank (2014). Table 4.10 provides an overview of the data used in our empirical models, their means, maxima, minima, and standard deviations.

Table 4.10: Descriptive statistics of variables used in the regression

Variable	N	Mean	Std. Dev.	Min	Max
GROWTH	1624	.022	.041	-.303	.321
log(GDP$_{pc}$)	1626	8.388	1.303	5.317	11.802
GINI(N)	1128	.374	.1	.169	.676
GINI(M)	1128	.44	.086	.188	.713
REDIST	1128	.066	.064	-.147	.261
REDIST(S)	453	.096	.073	-.025	.261
INVS	1625	.206	.111	-.013	.986
SCHOOLING	1584	5.9	3.063	.04	13.09
log(LIFEEX)	2027	4.127	.2	3.081	4.422
GOVC	1626	.205	.118	-.024	.934
INFL	1656	.361	2.624	-.066	69.628
OPEN	1822	.76	.486	.02	4.378
POLRIGHT	1624	4.084	2.195	1	8
log(FERT)	2029	1.283	.55	-.137	2.213
CREDIT	1521	.383	.377	.009	2.951
PSEDUC	1018	.045	.02	.006	.264

Appendix A-2: Usage of difference GMM and system GMM to estimate Equation 4.1

Our preferred econometric strategy used to estimate the marginal impacts of the variables included in Equation 4.1 is system GMM. To give a brief intuition on its basic assumptions and properties, first rewrite Equation 4.1 as

$$y_{it} = \theta y_{it-1} + \lambda h_{it} + \gamma \Psi_{it} + \delta R_{it} + \beta \mathbf{X}_{it} + \eta_i + \xi_t + v_{it}. \tag{4.3}$$

This equation, in principle, can easily be estimated by OLS. However, when working with macroeconomic data, unobserved heterogeneity η_i often yields biases if not accounted accurately for. A simple way to overcome this problem would be to use a within-group estimator or a first-difference approach such as Anderson and Hsiao (1982). However, whereas the former suffers from a Nickell (1981) bias when conducting dynamic panel estimations, first-difference transformations neglect the cross-sectional information in the data and magnify gaps in unbalanced panels. As a result, efficiency gains are possible when estimating the model in a Generalized Method of Moments (GMM) context.

A common approach to account for both unobserved heterogeneity and endogeneity in models with lagged dependent variables is the GMM estimator proposed by Arellano and Bond (1991).[30] Define that $\Delta k \equiv (k_{it} - k_{it-1})$ and $\Delta_2 k \equiv (k_{it-1} - k_{it-2})$, the basic idea of this approach is to adjust (4.3) to

$$\Delta y = \theta \Delta_2 y + \lambda \Delta h + \gamma \Delta \Psi + \delta \Delta R + \beta \Delta \mathbf{X} + \Delta \xi + \Delta v \tag{4.4}$$

and then to use sufficiently lagged values of y_{it}, h_{it}, Ψ_{it}, R_{it}, and $\mathbf{X}_{it}$ as instruments for the first-differences. However, differencing Equation 4.3 discards the information in the equation in levels. This drawback is particularly severe in the context of inequality studies, as most of the variation in inequality data stems from the cross section rather than the time-dimension. Moreover, Blundell and Bond (1998) and Bond et al. (2001) show that the difference GMM estimator can be poorly behaved if time-series are persistent or if the relative variance of the fixed effects η_i is high. The reason is that lagged levels in these cases provide only weak instruments for subsequent first-differences, resulting in a large finite sample bias.

[30] In the case of the growth-inequality nexus, two examples are Forbes (2000) and Panizza (2002).

System GMM proposed by Arellano and Bover (1995) and Blundell and Bond (1998) provides a tool to circumvent this bias if one is willing to assume a mild stationary restriction on the initial conditions of the underlying data generating process.[31] In this case, additional orthogonality conditions for the level equation in (4.3) can be exploited, using lagged values of Δk and $\Delta_2 k$ as instruments. In doing so, system GMM maintains some of the cross-sectional information in levels and exploits the information in the data more efficiently.

Satisfying the Arellano and Bover (1995) assumptions, system GMM has been shown to have better finite sample properties than difference GMM (see Blundell et al., 2 000). To detect possible violations of these assumptions, we conduct Difference-in-Hansen tests to assess the validity of the additional moment restrictions for each of the system GMM regressions.[32] To challenge a potential problem caused by "instrument proliferation" (Roodman, 2009a), we use two different strategies. The first strategy restricts the number of lags included in our analysis. More specifically, the moment conditions utilized in our system GMM approach can be formulated as follows: let $\tilde{\mathbf{X}}'_{it} \equiv [\Psi_{it}\ R_{it}\ \mathbf{X}'_{it}]$ and $\mathbf{\Xi}'_{it} \equiv [y_{it-1}\ \tilde{\mathbf{X}}'_{it}]$, the moment conditions in our analysis used for the regression in first-differences are

$$\mathrm{E}[(v_{it} - v_{it-1})\mathbf{\Xi}_{it-2}] = 0 \text{ for } t \geq 3,$$

and the additional moment conditions for the regression in levels are given by

$$\mathrm{E}[(v_{it} + \eta_i)(\mathbf{\Xi}_{it-1} - \mathbf{\Xi}_{it-2})] = 0 \text{ for } t \geq 3.$$

The second strategy is based on principal component analyses (PCA) to reduce the number of instruments and to exploit information from a larger lag number (Bai and Ng, 2010; Kapetanios and Marcellino, 2010). The PCA variant of our empirical specification uses four lags of all endogenous regressors. The number of utilized components is selected based on the Kaiser-Meyer-Olkin measure of sampling adequacy (Kaiser, 1974), and the portion of the variance that is explained by the utilized components. In addition, we follow the rule of thumb stressed by Roodman (2009b,a), emphasizing that the number of instruments should approach N to ensure that the model is neither over- nor underfitted.

[31] The assumption on the initial condition is $\mathrm{E}(\eta_i \Delta y_{i2}) = 0$, which holds when the process is mean stationary, i.e. $y_{i1} = \eta_i/(1-\theta) + v_i$ with $\mathrm{E}(v_i) = \mathrm{E}(v_i \eta_i) = 0$.

[32] A more detailed description of the estimator in the context of the empirical application can be found in Bond et al. (2001) and Roodman (2009b).

Appendix A-3: Standardization Procedure in the SWIID

Our preferred measures of income inequality and redistribution stem from the Standardized World Income Inequality Database (SWIID, Version 5.0, released in October 2014) generated by Solt (2009, 2016). The SWIID is based on the UN World Income Inequality Database (WIID), and several other cross-country inequality datasets, data provided by national statistical offices, and scholarly articles. As the source data is not directly comparable, Solt (2016) provides an algorithm to transform and adjust the original data, achieving estimates of net and market inequality comparable to those of the LIS Key Figures. A very rough overview of the standardization procedure can be given as follows: (1) The data is sorted into categories by welfare definitions and by equivalence scale. (2) Ginis of net and market inequality on the basis of household adult equivalent income from the Luxembourg Income Study (LIS) are added as a baseline, generating a dataset in which each country-year observation has data entries in at least one of thirteen categories. (3) Ratios between the variables in different categories are estimated as a function of country-decade, country, region and development status through various regression models. In further steps eleven series of estimates, comparable with the LIS net-income data, are calculated and combined into a single variable. (4) Possible measurement errors are corrected by using five-year weighted moving averages on all data points except those taken from the LIS and certain time periods. To fully reflect data uncertainty, the SWIID reports 100 different imputations for every observation, which are generated via Monte Carlo simulations.

Appendix A-4: Redistribution in the world, REDIST and REDIST(S)

Figure 4.7 illustrates the histogram of REDIST and REDIST(S) using 5-year averages, as in our empirical specification. When considering all country-years available in the SWIID, the mean value of redistribution is 6.56 percentage points. The standard deviation of 6.44, however, indicates that there are some major differences in the extent of redistribution across countries. The most expansive social system in the sample reduces market inequality by 26.07 percentage points, whereas some policies even yield an increase in inequality.

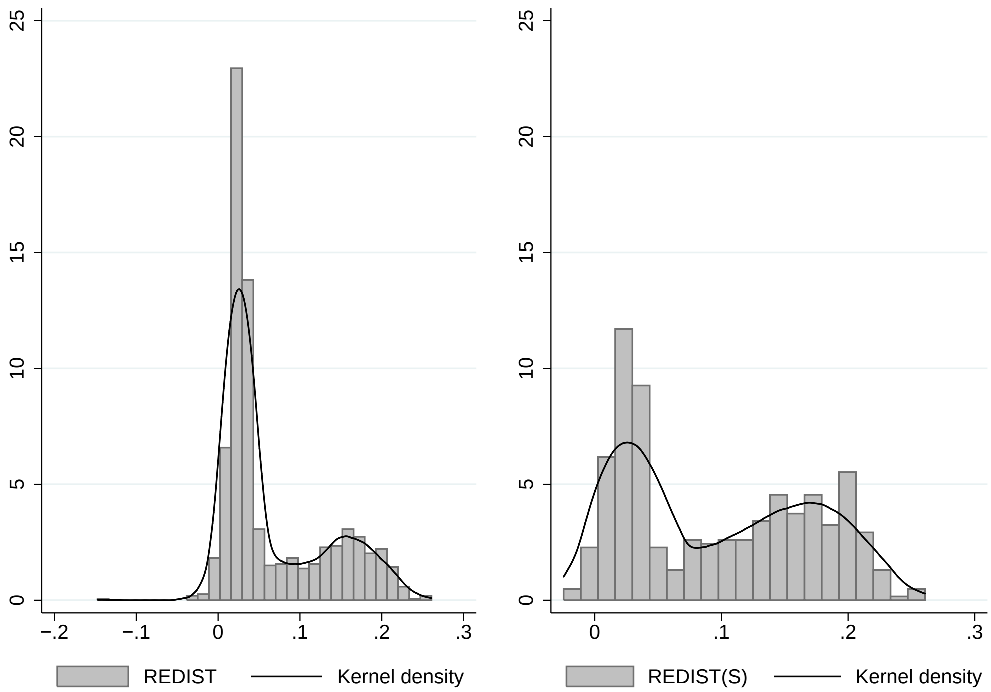


Figure 4.7: The distribution of REDIST and REDIST(S) across countries.
Notes: REDIST: N=1,128, skewness=1.043, kurtosis=2.847. REDIST(S): N=453, skewness=0.268, kurtosis=1.627. Kernel is Epanechnikov.

The data also highlights that there are substantial differences in the amount of redistribution between countries at different stages of development. Using the classification of the World Bank, the mean value of redistribution in the sample of high-income countries is 12.09 percentage points and substantially exceeds the mean redistribution level in low-income countries (3.62). As REDIST(S) is composed of a larger fraction of rich economies, the picture changes slightly when considering the subsample of redistribution data that includes only the most reliable observations. The mean value increases to 9.64, but the bimodal distribution is preserved. Whereas the sample now includes a higher frequency of observations with high levels of redistribution, REDIST(S) contains less data points in which inequality is enhanced by political intervention.

Table 4.11: Weak instrument diagnostic of the baseline results

	Model Specification of Baseline Table				
	(1a)	(1b)	(2)	(3)	(4)
	Panel A: Levels-Equation				
Weak IV tests					
Sanderson-Windmeijer F Stat (GINI(N))	9.25	6.32	4.80	20.65	24.34
Sanderson-Windmeijer F Stat (REDIST)	14.26	16.50	17.98	65.40	62.02
Stock-Yogo maximal IV relativ bias $\leq$ 30 percent	4.35	4.35	4.14	3.92	3.89
Under-identification tests					
Sanderson-Windmeijer χ^2 p-val (GINI(N))	0.000	0.000	0.000	0.000	0.000
Sanderson-Windmeijer χ^2 p-val (REDIST)	0.000	0.000	0.000	0.000	0.000
	Panel B: Difference-Equation				
Weak IV tests					
Sanderson-Windmeijer F Stat (GINI(N))	3.25	18.39	9.53	15.15	19.36
Sanderson-Windmeijer F Stat (REDIST)	27.56	51.30	53.92	21.00	37.43
Stock-Yogo maximal IV relativ bias $\leq$ 30 percent	3.99	3.99	3.95	3.93	3.92
Under-identification tests					
Sanderson-Windmeijer χ^2 p-val (GINI(N))	0.000	0.000	0.000	0.000	0.000
Sanderson-Windmeijer χ^2 p-val (REDIST)	0.000	0.000	0.000	0.000	0.000
	Panel C: Weak-instrument-robust tests				
AR-test p-val (Anderson and Rubin, 1949)					
Model	0.000	0.000	0.000	0.000	0.000
GINI(N)	0.000	0.000	0.000	0.000	0.000
REDIST	0.000	0.000	0.000	0.004	0.043
K-test p-val (Kleibergen, 2005)					
Model	0.094	0.094	0.000	0.000	0.000
GINI(N)	0.002	0.002	0.000	0.011	0.040
REDIST	0.000	0.000	0.000	0.077	0.046

	Panel D: Weak-instrument robust intervals		
	CLR (Moreira, 2003)	Wald	Level
Column (1a) with all observations			
GINI(N)	[-0.784; -0.007]	[-0.391; -0.094]	90%
REDIST	[-0.326; -0.057]	[-0.229; -0.011]	90%
Column (1b) with standardized observations			
GINI(N)	[-0.579; -0.039]	[-0.347; -0.101]	90%
REDIST	[-0.294; -0.015]	[-0.209; 0.016]	90%

Notes: Table reports weak instrument diagnostics. The Sanderson-Windmeijer tests are computed as described in Sanderson and Windmeijer (2016). The F-test extends the weak instrument test for individual regressors proposed by Angrist and Pischke (2009). Benchmark values refer to Stock and Yogo (2005). AR p-val reports the p-value of the Anderson and Rubin (1949) test, while the K-test refers to the test described by Kleibergen (2005). The tests are robust to weak instruments, i.e. they have the correct size in cases when instruments are weak, and in those when they are not. Weak-instrument robust intervals are computed following the conditional likelihood ratio test of Moreira (2003).

Table 4.12: Sensitivity analysis of the baseline results.

	System GMM (collapsed)		First-Difference GMM		3SLS (SEM)		Optimal Systems GMM	
	(1)	(4)	(1)	(4)	(1)	(4)	(1)	(4)
L.log(GDP$_{pc}$)	-0.00987	-0.0289***	-0.124***	-0.053***	-0.0000305	-0.0162***	0.5962***	-0.0153***
	(0.00834)	(0.00551)	(0.0293)	(0.0118)	(0.0014)	(0.00187)	(0.0128)	(0.0011)
GINI(N)	-0.569***	-0.00804	-0.448***	-0.164**	-0.0831***	-0.0158	-0.0817***	-0.0124
	(0.105)	(0.0611)	(0.1640)	(0.0659)	(0.0176)	(0.0163)	(0.01638)	(0.0096)
REDIST	-0.256**	0.0424	-0.1200	0.4380**	-0.1412***	-0.0517*	-0.1520***	-0.0492***
	(0.128)	(0.0647)	(0.2230)	(0.1700)	(0.0295)	(0.0280)	(0.0262)	(0.0105)
INVS		0.0524		0.0661		0.03734**		0.0421***
		(0.0362)		(0.0429)		(0.0153)		(0.0105)
SCHOOLING		0.00180		0.00856**		0.0013**		0.0010***
		(0.00226)		(0.00404)		(0.00063)		(0.0004)
log(LIFEEX)		0.0720**		0.0498		0.0269**		0.0263***
		(0.0290)		(0.0492)		(0.0123)		(0.0072)
GOVC		-0.0638		-0.00975		0.0062		0.0148
		(0.0389)		(0.0354)		(0.0138)		(0.0106)
INFL		-0.00244		-0.000917		-0.00081		-0.0007**
		(0.00213)		(0.000673)		(0.00079)		(0.0003)
OPEN		-0.00211		-0.000897		0.0089		0.0018
		(0.00555)		(0.00642)		(0.0019)		(0.0011)
POLRIGHT		0.000535		0.00129		-0.00109		-0.0010*
		(0.00148)		(0.00237)		(0.00082)		(0.0006)
log(FERT)		-0.0421***		-0.051***		-0.0305***		-0.0307***
		(0.0123)		(0.0194)		(0.00414)		(0.0027)
Observations	955	740	776	602	766	602	766	602
Countries	154	125	144	119	144	119	144	119
Hansen p-val	0.236	0.325	0.0245	0.317				
Diff-Hansen	0.640	0.475						
AR(1) p-val	0.000268	0.000191	0.017	0.00123				
AR(2) p-val	0.655	0.704	0.0326	0.82				
Instruments	39	116	35	95	27	99	27	99

Notes: Dependent variable is real per capita GDP growth. Table reports sensitivity analyses of the baseline results. Column numbers refer to the models of Table 4.2. The first two columns present results from two-step system GMM estimations with a collapsed instrument matrix (but full set of instruments). The second technique is difference GMM (Arellano-Bond). The third approach is 3SLS in a simultaneous equation model (SEM) using the same specification as the baseline model, but building on a linear system of equations (LSE) where each period t enters as a separate equation. The final method uses optimal systems GMM (OSGMM) estimation based upon the same LSE as the 3SLS estimator. (Robust) standard errors are given in parentheses. Hansen p-val gives the J-test for overidentifying restrictions. Diff-Hansen gives the Difference-in-Hansen statistic of the instrument subset for the level equation. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4.13: Impact of redistribution across different development levels, restricted sample

	(1a)	(1b)	(2)	(3)	(4)
	Panel A: Instrument matrix with reduced lag-structure				
REDIST(S)	1.894**	1.821***	1.491***	1.346*	0.527
	(0.840)	(0.457)	(0.568)	(0.784)	(0.712)
REDIST×L.log(GDP$_{pc}$)	-0.195**	-0.189***	-0.145**	-0.130	-0.0490
	(0.0898)	(0.0462)	(0.0599)	(0.0823)	(0.0741)
GINI(M)	-0.226***	-0.140**	-0.0617	-0.0580	-0.0299
	(0.0759)	(0.0670)	(0.0485)	(0.0517)	(0.0523)
Observations	434	374	374	374	374
Countries	73	67	67	67	67
Hansen p-val	0.071	0.133	0.939	1.000	1.000
Diff-Hansen	0.723	0.950	1.000	1.000	1.000
AR(1) p-val	0.000	0.000	0.000	0.000	0.000
AR(2) p-val	0.273	0.192	0.129	0.125	0.124
Instruments	62	62	92	166	181
Joint p-val	0.054	0.000	0.006	0.076	0.571
	Panel B: PCA-version of the instrument matrix				
REDIST(S)	1.197	1.309**	1.054*	1.324**	0.301
	(0.822)	(0.515)	(0.559)	(0.570)	(0.754)
REDIST×L.log(GDP$_{pc}$)	-0.122	-0.132**	-0.104*	-0.128**	-0.0323
	(0.0872)	(0.0561)	(0.0606)	(0.0567)	(0.0773)
GINI(M)	-0.221***	-0.134**	-0.0555	-0.0809	0.00157
	(0.0795)	(0.0599)	(0.0486)	(0.0647)	(0.0561)
Observations	434	374	374	374	374
Countries	73	67	67	67	67
Hansen p-val	0.279	0.640	0.700	0.349	0.398
AR(1) p-val	0.000	0.000	0.000	0.000	0.000
AR(2) p-val	0.296	0.155	0.113	0.151	0.212
Instruments	78	78	78	78	78
KM Stat	0.812	0.813	0.860	0.774	0.802
POV explained	1.000	1.000	0.991	0.921	0.915
Joint p-val	0.313	0.023	0.071	0.063	0.900

Notes: Dependent variable is per capita GDP growth. Table reports two-step system GMM estimations with Windmeijer-corrected standard errors in parentheses. All regressions include period fixed effects. Hansen p-val gives the J-test for overidentifying restrictions. Diff-Hansen gives the Difference-in-Hansen statistic of the instrument subset for the level equation. AR(1) p-val and AR(2) p-val report the p-values of the AR(n) test. Instruments illustrates the number of instruments. KM Stat displays the Kaiser-Meyer-Olkin measure of sampling adequacy (see Kaiser, 1974), POV gives the portion of variance explained by the utilized components. Joint p-val shows the p-values on the Wald test for joint significance of GINI(N) and its product with the moderator variable. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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