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*"ECB's Monetary Policy and Income Inequality: evidence from Panel Data
Models"*

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Chapter 1

Introduction

Since the 1980s, income inequality has been on the rise in most developed economies. In last decade, this phenomenon has increasingly drawn the attention of policymakers and researchers, to such an extent that it was labeled "the defining challenge of our time" by president Obama.¹

Beyond being an ethical issue, it is mainly an economic one. Recent studies on the consequences of income inequality show its negative effect on economic growth [7].

In particular, economists investigate the causes of income inequality in order to mitigate them and ensure an efficient transmission of fiscal and monetary policy.

Despite the increasing focus on this topic, central bankers have often overlooked the possible interaction between monetary policy and the growing income inequality, until very recently.

The main reason is that primary objective of central banks is the price and financial stability, whereas redistribution falls within the competence of fiscal policymakers.

Quoting Benoît Coeuré (2012): *"The task of the ECB under the Treaty on the Functioning of the European Union is to ensure price stability in the medium term. It thus focuses on income and wealth stabilisation rather than on the allocation of economic resources, or on redistribution."*

However, even though the distribution effects are not a clear mandate of central banks, financial analysis is normally conducted to gain a thorough outlook of the economic scenario, and in turn to achieve the monetary policy goals in the most efficient way.

In this sense, they assess real activity and financial conditions, taking into account distributional features.

For example, the European Central Bank (ECB) regularly reviews the fiscal policy, output

¹stated in occasion of a speech sponsored by the Center for American Progress, December 04, 2013.

and labour market conditions with the intent of evaluating the short to medium-term determinants of price movements.

As some of the most relevant ECB' s authorities stated:

"From a central banker' s perspective, the most relevant aspects of recent works concern the assessment that monetary policy can have sizeable distributional effects. Indeed, inequality has been largely ignored in discussions of monetary policy. But this might be changing." Yves Mersch (17 October 2014)

"Because the use of new instruments can have different consequences than conventional monetary policy, in particular with respect to the distribution of wealth and the allocation of resources, it has become more important that those consequences are identified, weighed and where necessary mitigated." Mario Draghi (14 May 2015)

Although studies on this matter are already available, the public debate is still ongoing as empirical conclusions appear still doubtful and in some cases contradictory to definitively answer the entire problem.

It proves to be complicated to isolate the issue and to obtain clear results.

The aim of the thesis is to contribute to the debate by evaluating the effect of monetary policy on income inequality in the Euro area, during the period from January 1999 to December 2015.

In order to better analyse the monetary policy during the entire sample period and compare the unconventional monetary policy implemented in recent years to the conventional one (that typically characterised the pre-financial crisis years), we employ a panel data model.

With respect to the existing literature this work aims to integrate empirical analysis with three main element of novelty:

- First, to capture the effect of unconventional monetary policies in the period of low interest rates after the crisis 2008, we used the shadow interest rate proposed by Wu and Xia (a new tool in the monetary policy analysis);
- Secondly, most of the current studies focused on the Federal Reserve (FED) or other central banks, instead the study of the effect of ECB' s monetary policy on income inequality is still at its origins;
- Lastly, since the Gini index is available only in annual frequency (for this reason we use the annual basis for all variables), we employed a panel data model of 11 European economies to cope with small length of time series and to consider the heterogeneity of European countries.

The results suggest a negative effect of the shadow interest rate on Gini coefficient. In particular, an increase (decrease) in the shadow rate leads to a decrease (increase) in Gini coefficient. From these considerations, a restrictive (expansive) monetary policy associated to an increase (decrease) in the shadow rate leads to a decrease (increase) in income inequality.

This paper is structured as follows: Chapter 2 introduces the main literature and explains the most relevant topics for the research; Chapter 3 describes the econometric model, reviewing the theoretical framework and its implications; Chapter 4 illustrates the data and empirical methodology; Chapter 5 shows the results and robustness checks; last chapter draws conclusions.

Chapter 2

Background and Literature Review

As previously introduced, the literature is at the beginning of the analysis, actually there are not so many empirical studies, in particular for the Euro area.

Now follows a briefly summary of the main literature that supported this thesis. Most of researches focus on the United States as Romer and Romer (1999), Coibon et al. (2012), Karen Davtyan (2016) and Nakajima (2015). They obtained different results as follows:

- Using first the United States (US) and then a large sample of countries, Romer and Romer (1999) study the effect of monetary policy on poverty and inequality.

They analyse for both the short and long run. The time-series from the US shows that expansionary monetary policy can lead to better conditions for the poor in the short run but at the same time monetary policy cannot produce permanent positive effect.

The cross-country analysis suggests that introducing monetary policy with the aim to decrease inflation and stabilise aggregate demand is the best way to improve conditions for the poor in the long run;

- Coibion et al. (2012), focusing on the FED, show that contractionary monetary policy shocks have enlarged income inequality.

Moreover they summarise five transmission channels through which these policies can have distributional consequences:

1) *income composition channel*: since there are different sources of income, monetary policy can affect them in different way. Actually high income households rely more in financial earnings than the poor that receive the most of income from labour earnings.

But since the monetary policy affects more the prices of assets can lead to a better conditions for the rich;

2) *earnings heterogeneity channel*: the inclination of the low income households to be more affected by economic cycle;

3) *portfolio channel*: the high income households holds more securities compare to the poor thus they can gain more from a expansionary monetary policy that can lead to an increase of asset prices;

4) *the savings redistribution channel*: a decrease of interest rates can change the nominal position of an individual. It can lead to a benefit for a borrower;

5) *financial segmentation channel*: since there are individuals more related to financial markets than other, they can benefit more from monetary policy shocks;

- Using Gini coefficient as measure for income inequality, Karen Davtyan (2016) examines the effect of conventional and unconventional monetary policy for the US. In particular, considering the large scale asset purchases, he accepts that these policies have modified the supply of short term and long term bonds and other assets, changing their prices.

But since usually the wealthy hold these assets, this can lead to a benefit for high income households.

The paper shows that the effect of expansionary non conventional policy increases the income inequality then the contractionary conventional one decreases it, but the effect of conventional monetary policy appears stronger than unconventional one;

- Starting from the paper by Coibon et al., Nakajima identifies two main general distributive channels of monetary policy.

One is the inflation channel that incorporates the financial segmentation, the portfolio and the savings redistribution channels.

Second is the income channel that incorporates the income composition and the earnings heterogeneity channels.

Inflation channel is identified with prices while income channel with the gross domestic product (GDP).

In addition to the studies on the US, Saiki and Frost (2014) focus on the effect of unconventional monetary policy on income inequality in Japan.

The paper shows that unconventional policies increased income inequality, in particular through portfolio channel.

Saiki and Frost declared that if unconventional monetary policy had an important role to restore financial market, these policies affected income distribution rising financial gain for high income households.

2.1 Income Inequality

Looking at figures 2.1 and 2.2 on the next page, that describes the trend of top 1% and 10% income share for some OECD countries, considering them as measures of income inequality, since the 1980s it is easy to observe an increasing trend.

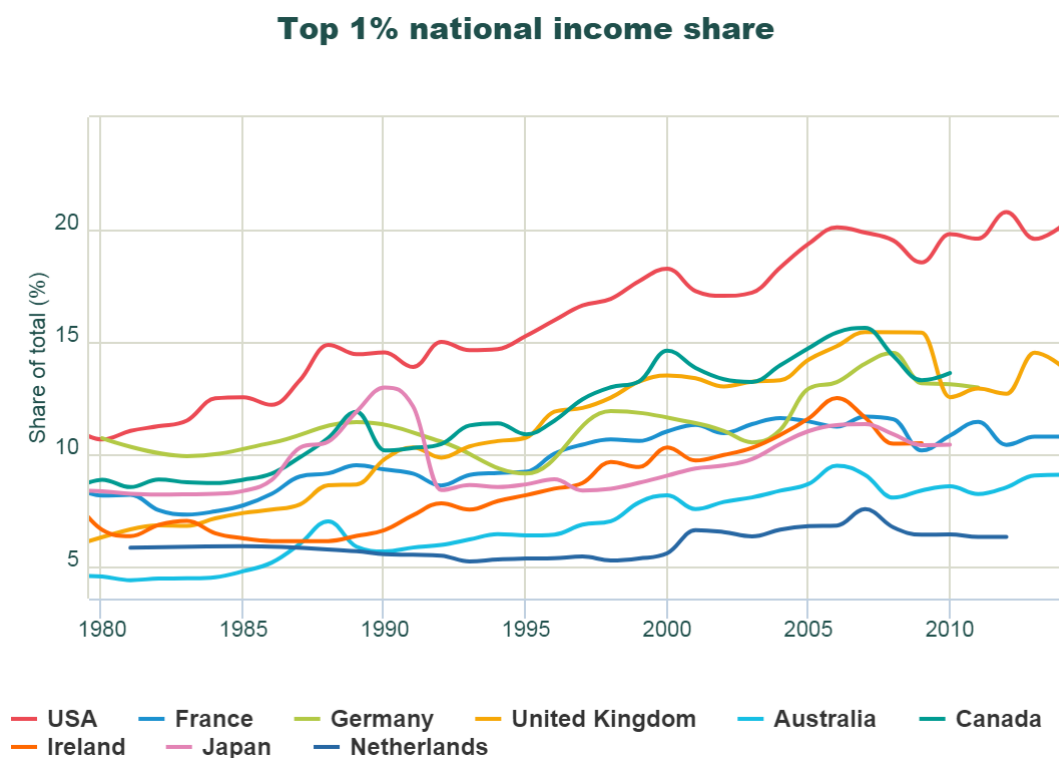


Figure 2.1: *Top 1% National Income Share*, source *World Income Database*.

Although income inequality is rising on the whole, there are some differences on the movements in single countries.

According to this, looking at figures 2.3 on the following page and 2.4 on page 9; while income inequality, measured by Gini index, has been steadily increasing in Italy and Spain or even declining as in France, differently in Australia, Japan, United Kingdom and the US where decisively increasing.

In particular since the 1999, the Gini coefficient has been relatively stable in the European countries as shown in figure 2.5 on page 10.

In this sense, it can be useful observing the Gini coefficient in the 1980 and in the 2014 for the countries belong to euro zone (those used in this thesis) compare, for example, to the US and Japan.

As shown in figure 2.6 on page 10, the values in the 2014 for the US and Japan is decisively increase relative to European Monetary Union (EMU) countries that show a low increase

Top 10% national income share

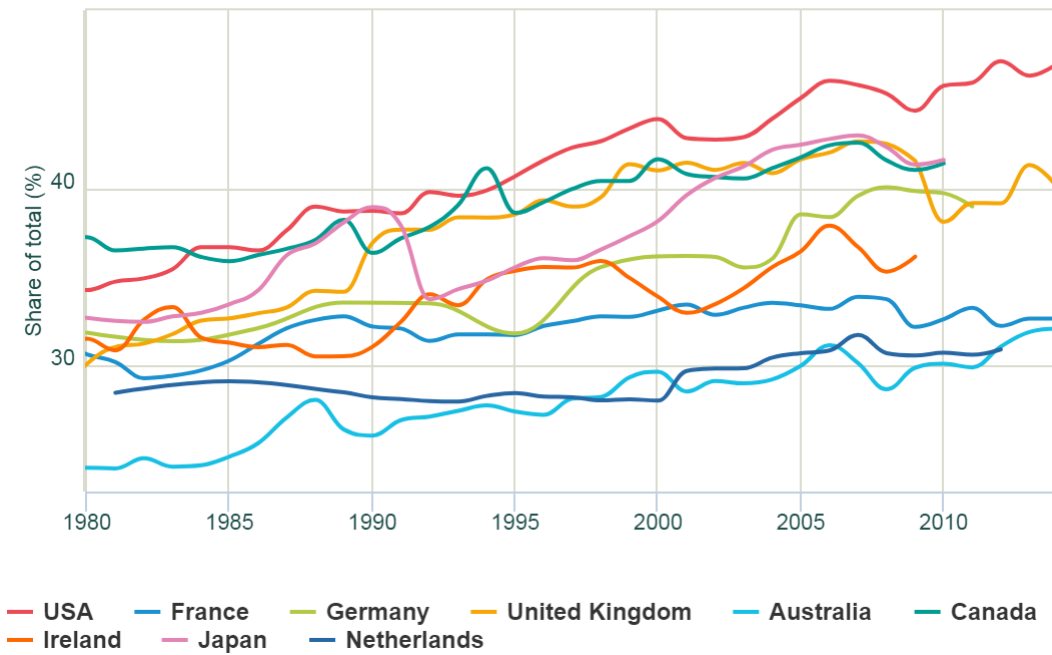
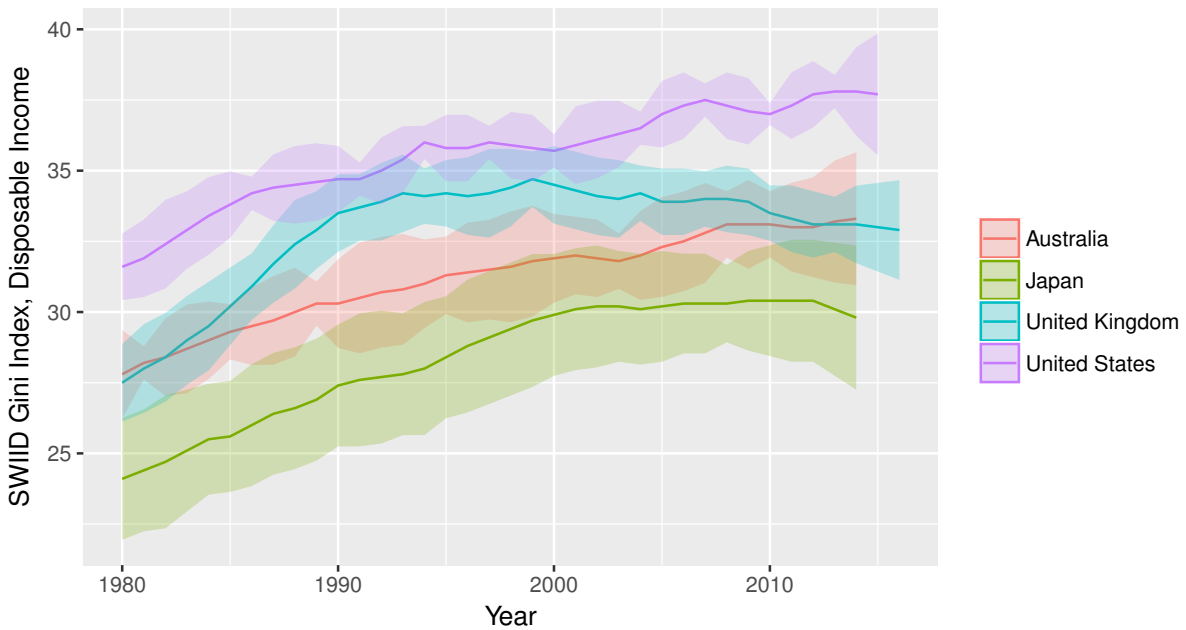


Figure 2.2: *Top 10% National Income Share, source World Income Database.*



Note: Solid lines indicate mean estimates; shaded regions indicate the associated 95% uncertainty intervals.
 Source: Standardized World Income Inequality Database v6.0 (Solt 2016).

Figure 2.3: *SWIID Gini Index on Disposable Income: Australia, Japan; United Kingdom and United States.*

or even a decrease as for France, Greece and Ireland.

Similarly, looking at the figure 2.5 on the following page, the increasing trend of Gini coefficient during the period 1999-2015 (the sample period considered for the thesis) for the European countries is nearly absent.

Furthermore, it is useful to observe in 2.7 on page 11 that Gini index on market income for the countries of our dataset exhibits a higher increase than Gini on disposable income 2.5 on the following page.

This shows that the distribution of income before taxes and transfers presents higher inequality.

Through the two figures we can observe this difference between gross and net Gini index.

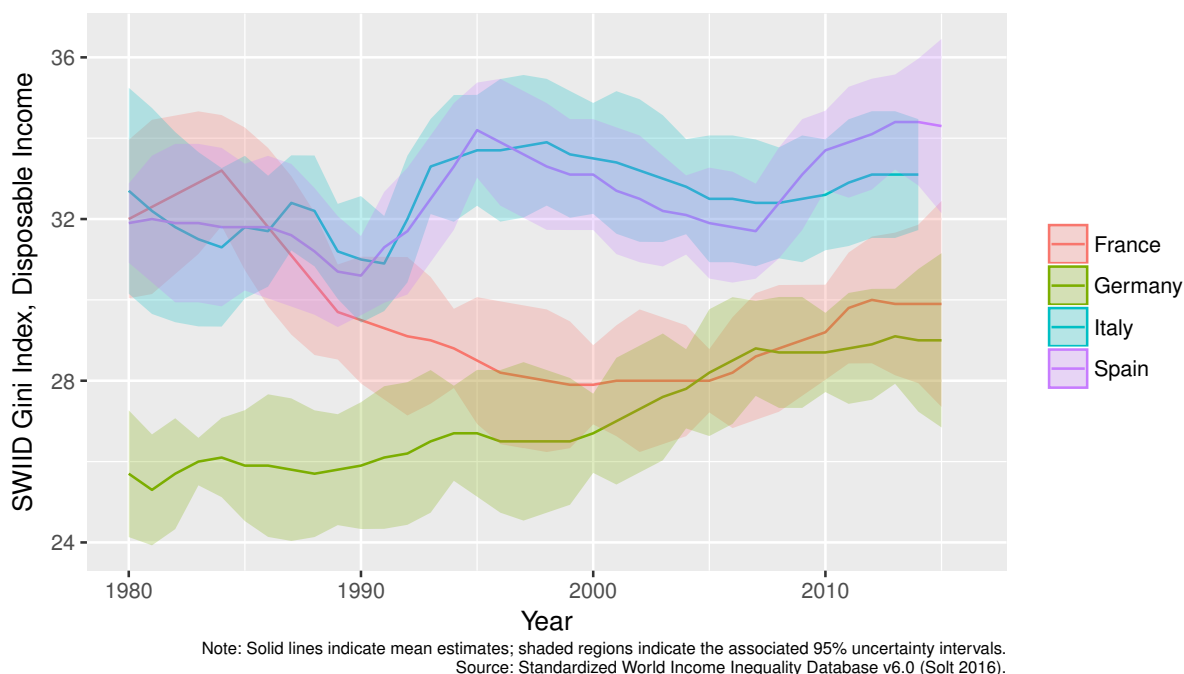


Figure 2.4: *SWIID Gini Index on Disposable Income: France, Germany, Italy and Spain.*

Income inequality is defined as a measure of income concentration. There are different measures to evaluate income inequality. The main indicator among researchers is the Gini coefficient.

Gini index measures the deviation within a country of the distribution of income among households from a perfectly equal distribution.

It was introduced by Corrado Gini and it is the most popular measure to evaluate income inequality. The Gini coefficient describes the area between the line of perfect equality and Lorenz curve. A Lorenz curve indicates the cumulative percentages of income held by the cumulative number of individuals, starting from the poorest ones.

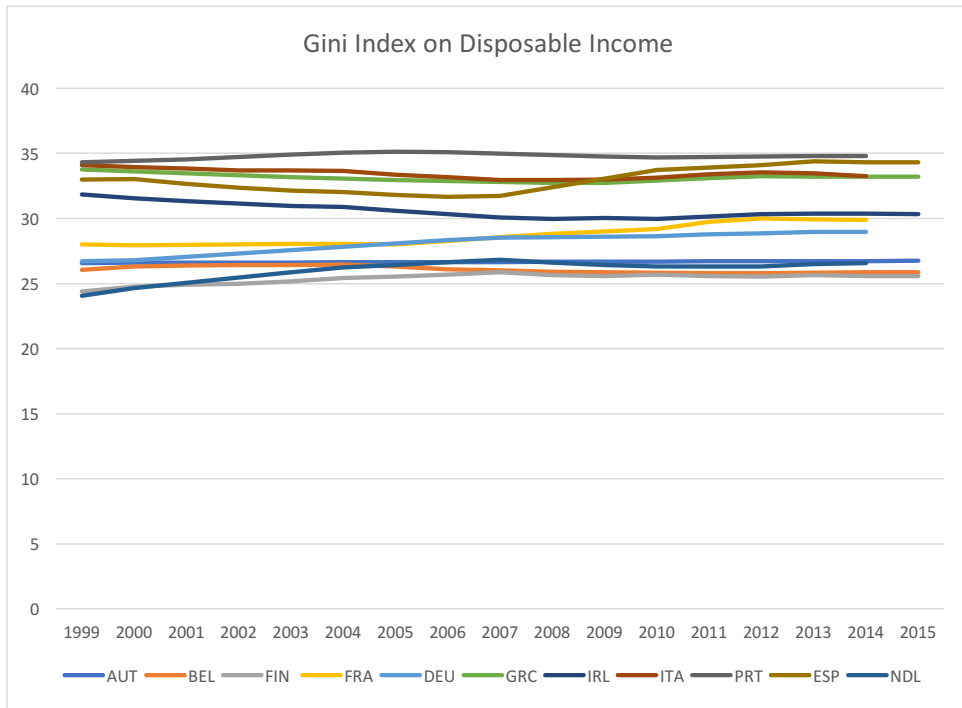


Figure 2.5: *Gini coefficient on disposable (net) income, source Standardised World Income Database for our dataset.*

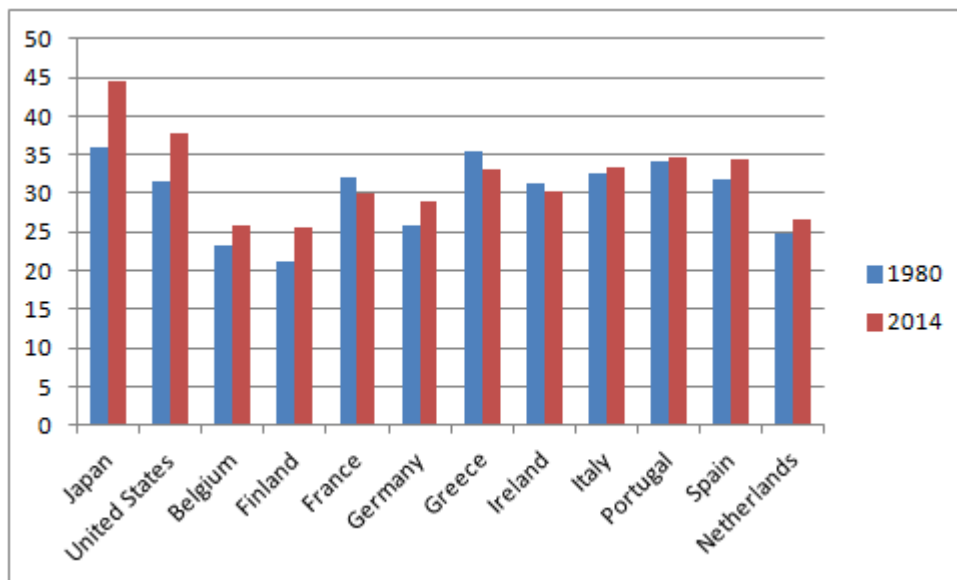


Figure 2.6: *Net Gini Index, comparison between countries of our dataset and US and Japan, source Standardised World Income Inequality for our dataset.*

It is a distributional measure and it describes the overall inequality, considering the entire population and it lies between 0 and 1 (sometimes is considered a scale from 0 to 100).

Full inequality corresponds to value 1, where all the income is associated to only one individual. Otherwise we have a situation of perfect equality, when the coefficient indicate a 0 value, in which all individuals receive the same amount of income.

In addition to Gini coefficient, researchers employ percentiles and deciles, evaluating what share of income goes to a certain percentage of population.

As opposed to the Gini coefficient, these measures take into account only one part of the entire population.

Often among researchers, talking about deciles, it is useful to consider the ratio between the ninth decile (i.e. the 10% of people with highest income) to that of first decile (i.e. the 10% of people with lowest income).

In this thesis we decided to use only Gini coefficient for two main reasons: first, it is the only measure that is available from 1999 to 2015 for our sample; second, it takes into account all the population.

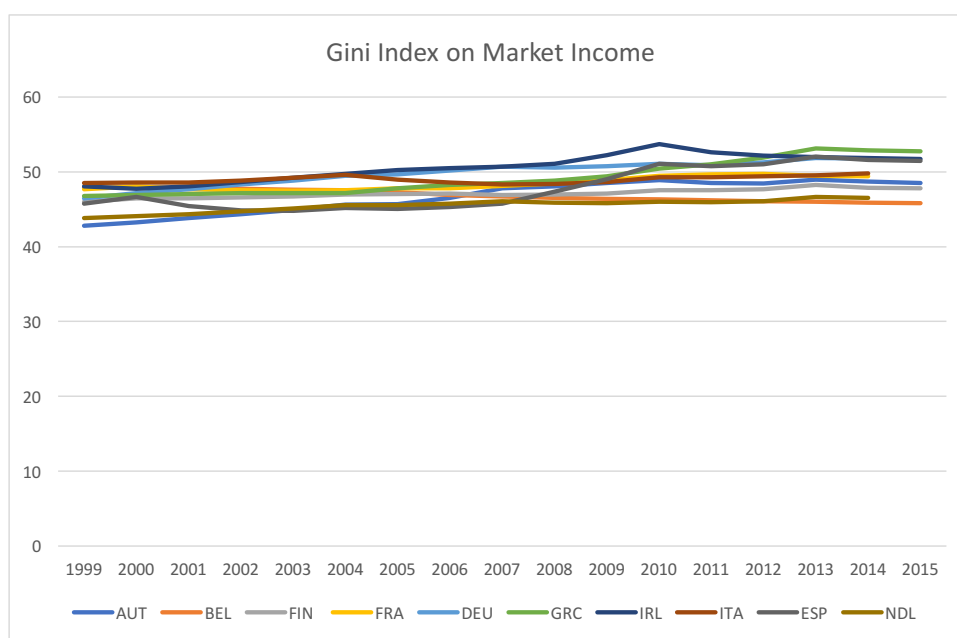


Figure 2.7: *Gini coefficient on market (gross) income, source Standardised World Income Database for our dataset.*

2.2 The ECB's Monetary Policy

2.2.1 Conventional Monetary Policy

The ECB's primary objective, sanctioned on the Treaty on the Functioning of the European Union, is to maintain price stability.

Focusing on this target, the ECB aims at maintaining inflation rates below, but close to 2% over the medium term.

The ECB has defined price stability as a year-on-year increase in the Harmonised Index of Consumer Prices (HICP) for the euro area.

In order to reach its task, ECB controls the short interest rates, thus, influencing the economy, it indirectly steers the inflation to its target in the medium term.

Furthermore, the ECB adopts a specific strategy to decide the value of interest rates. In this sense, it conducts two main analysis to take monetary decisions: economic analysis and monetary analysis.

The economic analysis evaluates the determinants of price developments in the short-medium term instead the monetary analysis identifies them in the long term. This strategy is based on the idea that in the sort and medium term inflation arises from the interaction between supply and demand in the financial and real markets instead the monetary base steers the inflation in the long term.

The official interest rates adopted by the ECB's Governing Council are:

- The interest rate on the main refinancing operations (MROs), the most relevant interest rate that signals the ECB's monetary policy stance;
- The rate on the marginal lending facility;
- The rate on deposit facility.

The main monetary policy instruments include:

- *open market operations*: they are the main instruments adopted by ECB. They include the main refinancing operations that provide the liquidity with maturity of a week and they are considered the main measures to steer the ECB's monetary policy. The long term refinancing operations (LTRO) have a maturity of three months thus they give an addition long term refinancing possibility to financial institutions;

- *standing facilities*: all the time monetary institutions can borrow liquidity from ECB, after presentation of eligible assets as collateral with an higher interest than MROs. There are two main standing facilities operations. The marginal lending facilities provide overnight liquidity from the ECB while the deposit facilities are operations that give the possibility to the banks to make overnight deposit with the central bank;
- *required reserves*: the ECB demands that financial institutions in the euro area hold minimum reserves on accounts with their national central banks.

2.2.2 Unconventional Monetary Policy

During the beginning of the crisis erupted in 2007, the main breakdown was due to malfunction of monetary market, increasing uncertainty of the liquidity among banks. But since September 2008, the intensification of the crisis has sharply accentuated anxieties in the money market.

In this context, the ECB responded assuming a fundamental role providing the liquidity to the single banks.

As a matter of fact, the ECB started to conduct MROs through auctions with fixed rate, providing all the liquidity asked by banks.

Starting from the collapse of US sub-prime mortgage market, central banks employed unconventional monetary policies in order to cope with the increasing financial instability. In addition to the regular conventional LTROs, since March 2008, the ECB implemented the LTROs with longer maturity.

To cope with rising illiquidity in the euro area system the ECB introduced the LTROs with six month maturity and then in May 2009 it extended the maturity until one year. Notably, between the end of 2011 and the beginning of 2012, the ECB provided one thousand billions with a 1% rate for the European banks.

Furthermore, other measures were employed, intervening directly to some securities markets.

The Covered Bond Purchase Programme (CBPP) was announced on 7 May 2009, it aimed to ease credit conditions for the banks in the euro area.

On 10 May 2010, the ECB announced the Securities Markets Programme (SMP), responding to the rising worries on the government bonds market.

As a matter of fact, markets started to mistrust the solvency of the governments with high deficit in the euro zone. In this context, the ECB decided to start with purchases of government bonds in the secondary markets.

All of these operations under the SMP were sterilised with absorbing measures.

On 2 August 2012 the ECB announced the Outright Monetary Transactions (OMT), they consists in unlimited purchases of government bonds with short maturity (1 and 3 years) under the EFSF/ESM¹ programme.

"Within our mandate, the ECB is ready to do whatever it takes to preserve the euro. And believe me, it will be enough" Mario Draghi (26 July 2012)

This intervention helped to restore the bonds market and to guarantee a good monetary policy transmission.

In order to safeguard and increasing the support to reach the price stability, ECB extended its non standard measures to both private and public sector, employing the so called asset purchase programme (APP).

It includes the following programmes:

- *Third covered bond purchase programme* (CBPP3) started on 20 October 2014 buying covered bonds. This programme started after the first covered bond purchase programme (CBPP1) in 2009 and the second covered bond purchase programme (CBPP2) in 2011;
- The *asset-backed securities purchase programme* (ABSPP) was introduced on 21 November 2014;
- On 9 March 2015 the ECB started to buy public sector securities with the introduction of *public sector purchase programme* (PSPP);
- *Corporate sector purchase programme* (CSPP) was introduced on 8 June 2016.

The targeted longer-term refinancing operations (LTROs) were an other measure adopted by ECB in order to enlarge its accommodative monetary policies and reinforce the good transmission of monetary policy. They provided further liquidity to credit institutions up to four years.

The first programme of this measure was introduced on June 2014 and a second programme on March 2016.

A first series of TLTROs was announced on 5 June 2014 and a second series (TLTRO II)

¹the European Financial stability Facility (EFSF) and European Stability Mechanism (ESM), the intergovernmental organisations to safeguard and provide a financial sustain for euro zone countries in financial distress.

on 10 March 2016.

They are called targeted because the liquidity that credit institutions could borrow is related to their loans to real economy (non-financial corporations and households).

2.3 Shadow Interest Rate

As previously described, the main monetary policy instrument is the short interest rate. Policy makers handle it to steer monetary policy and control inflation.

Central banks lower it in order to sustain the economy and increase it to slow down activity. Since the beginning of the last financial crisis, most of the central banks cut the policy rates close to 0, reaching the so-called Zero Lower Bound (ZLB)².

Consequently monetary policymakers, who cannot lower the policy rate further, introduced different unconventional policies to stimulate the economy even more.

Hence, this new monetary policy environment with the introduction of new monetary measures along with the reduction of policy rate up to 0, made the evaluation of the monetary policy stance more complicated.

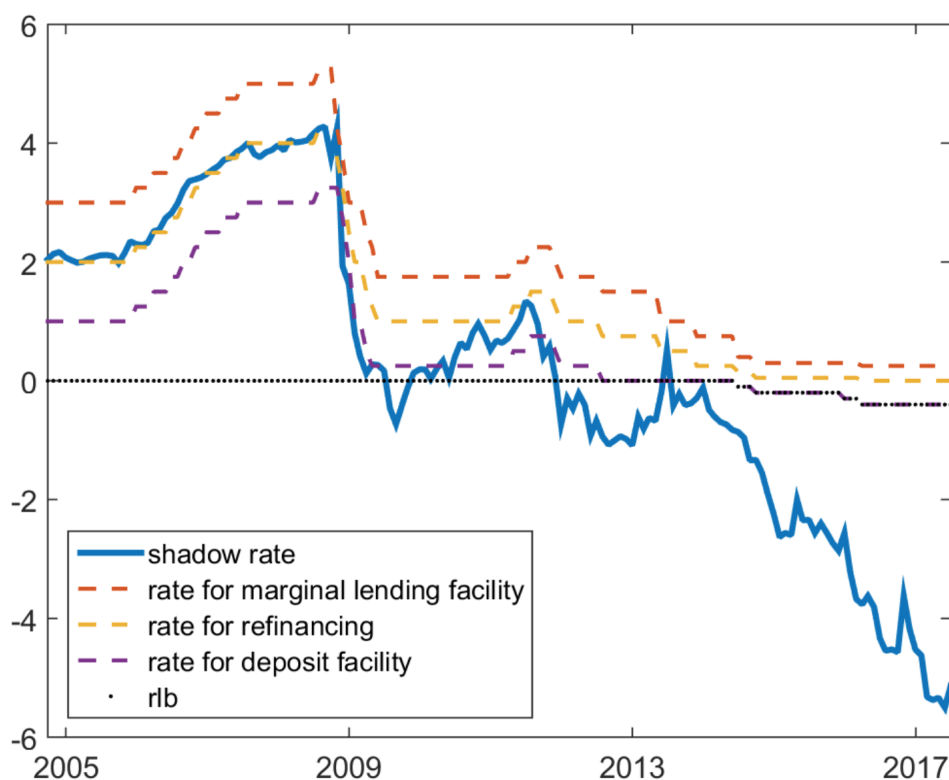


Figure 2.8: Shadow Interest Rate.

Among researchers it was common to use the policy rate as measure of the monetary

²the situation where the short-term interest policy rate is at or near 0.

policy guidance, but since unconventional monetary policies are not reflected in the main refinancing operations rate, thus it can not be used as policy measure.

In this sense in order to capture the unconventional monetary policy effects, we adopted the *Shadow Interest Rate* proposed by Jing Cynthia Wu and Fan Dora Xia³.

This rate is developed for the FED, the Bank of England and for the ECB.

When the policy rates are above the zero lower bound, the shadow rate is nearly the same of the MROs rate otherwise when the policy rates reach the zero lower bound and in particular with the adoption of unconventional measures, using an unobserved components model and taking informations from term structure of interest rates, the Wu-Xia shadow rate becomes negative.

In this way, it is possible to use an effective rate to measure the monetary policy stance during the entire period, considering both the conventional and unconventional monetary policy.

As shown in the figure 2.8, with the introduction of SLTROs (2009) and LTROs (2011), the Wu-Xia shadow rate reached negative values. Furthermore the ECB shadow rate dropped in negative territory in 2012, following the announcement of OMT operations and their implementation.

Finally the shadow interest rate moved sharply negative when the ECB started with Quantitative Easing programme during 2015.

³Measuring the Macroeconomic Impact of Monetary Policy at the Zero Lower Bound, available at <https://www.imf.org/external/np/res/seminars/2015/arc/pdf/Xia.pdf>.

Chapter 3

Econometric Model

3.1 Panel Data Model

Panel data models refer to data that are related to a set of individuals observed over two or more periods of time.

They are also called "cross-sectional time series data" because they result from the union of cross-sectional and time series data.

In this sense panel data models are based on two dimensions: the N dimension that indicates individuals, whereas T specifies the time dimension.

If T is equal for all N cross-sectional units, panel data is balanced.

Studies of microeconomic problems rather than macroeconomic ones lead to distinguish between two type of panel data as the different set of data used in the two settings. Microeconomic panel data are based on a setting with a N dimension greater then T , instead macroeconomic panel data models relay on T greater than N . This distinction is relevant for the properties of the estimator.

There are several advantages employing panel data rather then the single times series or cross sectional data models.

First, panel models allow to consider more data ($N \times T$), benefiting from an increase in efficiency of parameters estimates; furthermore, including more information, they can control for unobserved heterogeneity among individuals.

Time series analysis does not allow to control for this type of individual heterogeneity, not even the cross-section analysis can study it because often this factors are unobservable.

Only with panel data structure, even in absence of specific informations this unobserved heterogeneity can be included in the model.

Consequently, panel models show variability both for the time dimension and for the cross-sectional one.

Aforementioned variability can be represented considering the error term as the summary

of three different components: a simple pure component v_{it} , the error term is composed of an unobservable time-invariant component α_i and an unobservable component λ_t that varies over time and it is the same among individuals.

$$\varepsilon_{it} = \alpha_i + \lambda_t + v_{it}, \quad (3.1)$$

The presence of only one component between α_i and λ_t produces the so called "*one way*" models, whereas the "*two way*" models consider both the components.

These models allow to control for unobserved features, as cultural and geographic factors, different business models among companies or national policies.

As a matter of fact, the main problem that arises when estimating the model with Ordinary Least Square (OLS) estimator is to control for unobservable characteristics that may correlate with the variables included in the regression.

The phenomenon of omitted variables is very common and causes a problem of endogeneity but it can be solved using the panel data.

Two main complications arise when these models are employed: first, estimators are inconsistent when regressors cannot be considered strictly exogenous; second, in the presence of cross section dependence where errors are correlated to different cross section units, the results can lead to misleading inference.

3.1.1 Panel Data with Strictly Exogenous Regressors

Considering y_{it} as the observation on the i^{th} individual unit at time t for $i = 1, 2, \dots, N$; $t = 1, 2, \dots, T$, the following is a panel data regression model

$$y_{it} = \alpha_i + \beta' x_{it} + v_{it}, \quad (3.2)$$

where α_i describes an unobservable, individual time-invariant effect, x_{it} identifies $k \times 1$ vector of observed unit individual regressors on the i^{th} cross-sectional unit, β is the k -dimensional vector of unknown parameters and v_{it} is the individual error term at time t . The unit-specific effect α_i accounts for the individual time-invariant effect that is not considered in the regression [8].

For these regressions and estimators, it is assumed that $E(v_{it} | X_i) = 0$, for all i and t , thus all the regressors are assumed strictly exogenous.

In this sense, the error term is assumed to be uncorrelated with all lags of explanatory variables.

Starting from this baseline panel data observations we can use two main models: Fixed effect model and Random effect model.

Fixed Effect Model

Before introducing the two models we describe the simple and basic one for panel data. The pooled OLS model exploits the OLS properties. Pooled OLS can be described as

$$y_{it} = \beta' x_{it} + v_{it}, \quad (3.3)$$

where y_{it} is the observation of dependent variable for the cross-sectional unit i at period t , x_{it} is a vector $1 \times k$ of independent variables, β is a vector of $k \times 1$ parameters and v_{it} is the error term.

But this model presents a relevant disadvantage, indeed for the validity of the model, the individual specific effect α_i is assumed to be uncorrelated with the regressors, thus $E(x_{it}\alpha_i) = 0$.

If this correlation is present, the pooled OLS model will be inconsistent, leading to the so called "heterogeneity bias".

The bias is due to the omission of the time-invariant variable [9].

In the Fixed Effect model (FE), α_i the time-invariant variable is considered to be correlated with the regressors, thus this model only requires that the explanatory variables are strictly exogenous $E(v_{it} | X_i) = 0$.

Starting from (3.2), the main idea of FE is to estimate β after eliminating the individual effect. Applying the average over time in the (3.2)

$$\bar{y}_i = \bar{\alpha}_i + \beta' \bar{x}_i + \bar{v}_i, \quad (3.4)$$

where \bar{y}_i , \bar{x}_i and \bar{v}_i are the averages over time.

FE model subtracts (3.4) from (3.2) obtaining the following equation:

$$y_{it} - \bar{y}_i = \beta'(x_{it} - \bar{x}_i) + (v_{it} - \bar{v}_i), \quad (3.5)$$

This is known as fixed effect or within estimator (within transformation). In order to estimate β , pooled OLS is applied to the above equation (3.5).

It can be computed the within estimator including N dummy variables for each unit as in the following regression:

$$y = \sum_{i=1}^n \alpha_i d_i + X\beta + v, \quad (3.6)$$

where d_i is an $NT \times 1$ vector of a dummy variable composed by all its elements equal to zero except for the elements that correspond to the i^{th} cross sectional unit.

Using this method the estimator is called the Least Square Dummy Variable (LSDV).

β , employing the LSDV model, is estimated using OLS and it corresponds to the same

estimate using the FE estimator.

Random Effect Model

Contrary to the FE, the Random Effect model (RE) assumes that the individual specific effects are uncorrelated with the regressors, $E(\alpha_i | X_i) = 0$.

The individual-specific effects are considered as realisations from a probability distribution function with a fixed number of parameters, distributed independently of the independent variables.

To obtain unbiased and efficient estimates, RE model applies the Feasible Generalised Least Squares (FGLS) technique, thus first transforming the model and then applying the OLS.

The transformation is equal to a "nearly differentiation":

$$y_{it} - \theta \bar{y}_i = (1 - \theta)\alpha_i + \beta'(x_{it} - \theta \bar{x}_i) + (v_{it} - \theta \bar{v}_i), \quad (3.7)$$

It is clear that if $\theta = 1$, FGLS estimator corresponds to LSDV estimator.

To guarantee the consistency of the RE estimator, regressors should not be correlated to the individual-specific term α_i .

Otherwise the assumption $E(\varepsilon_{it} | X_i) = 0$ would be violated.

This assumption is not relevant in the FE model where the individual specific effect α_i has not a distribution.

Consequently the disadvantage of RE model is to support this assumption, that sometimes can appear doubtful to keep.

For example, in the macroeconomic context, FE model seems to be more appropriate than RE model: first, if the individual effect α_i represents omitted variables, the specific characteristics of countries probably appear to be correlated to the other regressors; second, it is difficult to think that the selected countries originate from a random panel because usually they are the most part of the countries used for the specific research.

Driskoll and Kraay Estimator

According to Pesaran (2015), heterogeneity across units was confined to unit-specific intercepts, treated as fixed or random.

With the increasing availability of data (across countries, regions, or industries), the panel literature moved from predominantly micro panels, where the cross dimension (N) is large and the time series dimension (T) is small, to models with both N and T large, and it has been recognised that, even after conditioning on unit-specific regressors, individual

units, in general, need not be cross-sectionally independent.

Ignoring cross-sectional dependence of errors can have serious consequences, and the presence of some form of cross-section correlation of errors in panel data applications in economics is likely to be the rule rather than the exception.

In line with the above literature, it is often not feasible suppose the presence of cross sectional independence of error terms in a panel data model, in particular in the macroeconomic context.

In this sense, ignoring the presence of cross sectional dependence can lead to bias estimates of the standard panel estimators.¹

As a matter of fact, supposing that the unobservable common factors are uncorrelated with explanatory variables, these estimates remain consistent but become inefficient.

In order to obtain statistical relevant results, taking into account cross sectional dependence in the residuals, research developed adjustments in standard errors.

Starting from this problem, Driscoll and Kraay (1998) studied a nonparametric covariance matrix estimation producing heteroscedasticity consistent standard errors that are robust to general cross sectional dependence.

The Stata software provides some corrections to cope with violating assumptions of the econometric model when there is the presence of heteroscedasticity and serial correlation. Daniel Hoecle² developed the program *xtscc* in Stata, correcting standard errors with Driskoll and Kraay estimator, with the aim to perform pooled OLS or fixed effects (within) regression models.

With this new Stata programme, he added the possibility to apply the Driskoll and Kraay's covariance matrix estimator to the unbalanced panel data models.

Considering the Driskoll and Kraay's conclusions for small balanced panel data models, the Monte Carlo experiments by Daniel Hoecle showed that disregarding the cross sectional dependence in a panel data can lead to overestimate the standard errors.

Even the Driskoll and Kraay's estimator lightly overvalues the estimates of the standard errors, however it performs better than the standard estimators in the presence of cross sectional dependence.

Starting from the assumption that it is inappropriate assuming that residuals of a panel data model are cross sectional independent, it is often better to consider correlation between and within groups, especially in the macroeconomic framework.

Driskoll and Kraay 's (1998) formulation shows as the standard time series covariance matrix estimator can be adjusted to cross sectional dependence in order to obtain robust estimates.

This methodology allows the error structure to be heteroscedastic, autocorrelated and

¹e.g. fixed effects (Fe) estimator, random effects (Re) estimator, or pooled OLS estimation.

²Daniel Hoecle, University of Basel, Robust Standard Errors for Panel Regressions with Cross-Sectional Dependence, The Stata Journal.

with cross-sectional dependence.

The Stata programme *xtscc* with *fe* option applies the within estimator (fixed effects regression model), considering Driscoll and Kraay's covariance matrix of the standard errors.

To do so, when *fe* option is applied, the Stata command *xtscc* works in two steps.

Firstly it modifies variables using *xtreg*, thus applying the within transformation

$$\tilde{z}_{it} = z_{it} - \bar{z}_i + \bar{z}. \quad (3.8)$$

Given that the within-estimator coincides to the OLS-estimator of:

$$\tilde{y}_{it} = \tilde{x}'_{it}\theta + \tilde{\varepsilon}_{it}, \quad (3.9)$$

the second step of the comand estimates the transformed regression (3.9) by pooled OLS estimation with Driscoll and Kraay standard errors.

3.1.2 Dynamic Panel Data Model

In addition to the static panel data model, often we are interested to examine the dynamic behaviour.

In this sense, we have to include the lagged dependent variables in the generating model in order to capture the dynamic attitude.

As a consequence of increasing disposable data, during last decade there was a growing interest on these kind of models.

However, even if we are not interested to estimate the coefficient of the lagged dependent variable, dynamic panel model can be fundamental to obtain consistent estimates of the other parameters.

As a matter of fact, if we don't consider this dynamic behaviour when is significant, we get biased estimates.

Although these models can better describe the dynamic dependence among variables, an endogeneity problem can occur when we employ them.

The presence of lagged values of the dependent variable, $y_{i,t-1}$, among the regressors will be correlated with the unit-specific effects, α_i , whether they are fixed or random, and with lagged u_{it} .

Dynamic panel model with one lagged dependent variable, $y_{i,t-1}$, and the regressors,

x_{it} ³, follows this structure:

$$y_{it} = \rho y_{i,t-1} + x'_{it}\beta + (\alpha_i + v_{it}) \quad (3.10)$$

Consequently both OLS and FGLS estimates are biased.

Actually in the case of pooled OLS, the bias concerns the correlation between dependent variable and the specific-individual effect α_i (if y_{it} correlates with α_i , y_{it-1} correlates with it as well).

Considering the LSDV estimator, the differentiation drops out the α_i term,

$$y_{it} - \bar{y}_i = \beta'(x_{it} - \bar{x}_i) + (v_{it} - \bar{v}_i), \quad (3.11)$$

in this case the bias arise from the correlation between the lagged dependent variable $y_{i,t-1}$ and the lagged error term v_{it-1} that contributes to develop \bar{v}_i .

The bias decreases with increasing of time periods T because the v_{it-1} term will less contribute to shape \bar{v}_i .

The strategy to cope with the endogeneity problem is based on taking into account for instrumental variables.

The main characteristics of these variables are the uncorrelation with error term and the correlation with variables that show endogeneity.

In this sense, it is developed a regression of original variables using instrumental variables. Then, substituting the estimates, it can be applied OLS to the model. It is developed a so called Two Stages Least Square (2SLS).

The main problem is linked to identify the correct instruments to employ in the model, remembering that the number of instruments has to be equal or greater then endogeneity variables.

Wide literature has examined the problem of endogeneity in dynamic panel models, introducing instrumental variables method (IV) and the Generalised Method of Moments (GMM).

Anderson and Hsiao, starting from the following model⁴

$$y_{it} = \lambda y_{i,t-1} + \beta' x_{it} + \varepsilon_{it}, \quad (3.12)$$

$$\varepsilon_{it} = \alpha_i + v_{it}, \quad (3.13)$$

introduced an IV method. Actually, applying the first difference to eliminate the individual-specific effect α_i ,

$$\Delta y_{it} = \lambda \Delta y_{i,t-1} + \beta' \Delta x_{it} + \Delta v_{it}, \quad (3.14)$$

³ x_{it} are strictly exogenous, thus uncorrelated with v_{it} .

⁴ α_i and v_i are assumed to be independent of each other.

the endogeneity problem remains $E(\Delta y_{i,t-1} \Delta v_{it}) \neq 0$.

To deal with the correlation between $\Delta y_{i,t-1}$ and Δv_{it} , Anderson and Hsiao (1981) proposed employing an instrumental variables (IV) method.

Considering that $E(y_{i,t-2} \Delta v_{it}) = 0$ and given that $y_{i,t-2}$ correlates with $\Delta y_{i,t-1}$, then $y_{i,t-2}$ can be a valid instrument for $\Delta y_{i,t-1}$.

Arellano and Bond extended the literature on the dynamic panel models.

Differently from Anderson and Hsiao, Arellano and Bond (1991) consider that additional instruments can be used to cope with above mentioned endogeneity problem.

They proposed a GMM approach based on all available moment conditions.

Starting from:

$$y_{i3} - y_{i2} = \lambda(y_{i2} - y_{i1}) + \beta' \Delta x_{i3} + \Delta v_{i3}, \quad (3.15)$$

$$y_{i4} - y_{i3} = \lambda(y_{i3} - y_{i2}) + \beta' \Delta x_{i4} + \Delta v_{i4}, \quad (3.16)$$

$$y_{i5} - y_{i4} = \lambda(y_{i4} - y_{i3}) + \beta' \Delta x_{i5} + \Delta v_{i5}, \quad (3.17)$$

$$\dots \quad (3.18)$$

$$y_{iT} - y_{i,T-1} = \lambda(y_{i,T-1} - y_{i,T-2}) + \beta' \Delta x_{iT} + \Delta v_{iT}, \quad (3.19)$$

In equation (3.15), y_{i1} is a valid instrument for $y_{i2} - y_{i1}$; in equation (3.16), y_{i1} and y_{i2} are valid instruments for $y_{i3} - y_{i2}$; in equation (3.17), y_{i1}, y_{i2} and y_{i3} are valid instruments for $y_{i4} - y_{i3}$ and so on until the equation (3.19) where the valid instruments are $y_{i1}, y_{i2}, \dots, y_{i,T-2}$. In this way, for each additional time period, there is an additional valid instrument.

Bias Corrected LSDV Estimator

A common feature among IV and GMM estimators is the weakness of their properties for panel data models with a small number of individuals, as is the case for macroeconomic panel data.

With the increasing interest for the dynamic panel models, partly thanks to the improving of the data availability, it was proposed a different approach to cope the problem of small sample.

Since the LSDV estimator is unbiased in the presence of lagged dependent variable, it has a relatively small dispersion compared to the other estimators.

LSDV's dispersion is often smaller compared to that of Anderson and Hsiao's estimator with instrumental variables and GMM that are consistent with $N \rightarrow \infty$.

Nickell (1981) suggested an expression of order T^{-1} for the inconsistency of LSDV for N , in the presence of the lagged dependent variable. But this expression did not consider of all terms that provide LSDV' bias.

Alongside the term of order T^{-1} , Kiviet (1995) studied even the terms of order $N^{-1}T^{-1}$

and $N^{-1}T^{-2}$. Consequently, to obtain a corrected LSDV estimator (LSDVC), the above terms are subtracted to the LSDV estimate.

The Monte Carlo experiment by Judson and Owen (1999) strongly suggest LSDVC when the number of individuals N is small as in the macro context.

Bruno (2005) extended the Bun and Kiviet (2003) studies to the unbalanced panels. Furthermore, Bruno has proposed a Stata command `xtlsdvc`⁵ that implements LSDVC based on the approximation proposed by Bruno (2005).

Through a Monte Carlo experiment, Bruno (2005) showed the performance of LSDVC compared to LSDV, Arellano and Bond estimator, Anderson and Hsiao estimator and Bundel and Bover estimator for unbalanced panel data model with small number of individuals N (10 and 20 cross sectional units), broadening the studies by Judson and Owen (1999).

⁵Giovanni S. F. Bruno (2005), Estimation and Inference in Dynamic Unbalanced Panel Data Models with a Small Number of Individual.

Chapter 4

Data and Empirical Model

This part shows the structure of the data and applied methodology, following the above literature and the available dataset.

In order to obtain the correct estimates of the unknown parameters, we have developed many models and tests.

4.1 Dataset and Model Specification

In order to analyse the effect of ECB's monetary policy on income inequality we considered the period from January 1999 to December 2015.

Choosing the first countries in the Euro area with higher GDP, we selected a panel of 11 countries: Austria, Belgium, Finland, France, Greece, Ireland, Italy, The Netherlands, Portugal and Spain.

Since 1 January 1999 the ECB started to implement monetary policy in the euro area, however the European Monetary Union (EMU) countries continued to maintain their fiscal policy.

In this sense, even if we are interested in the role of monetary policy, we developed a panel data model in order to capture the differences among EMU countries.

We selected the entire period in which the ECB has operated, in order to analyse the overall monetary policy relying, on more available data.

The dependent variable of the model is the GINI coefficient that identifies income inequality. It is available only in annual frequency, consequently all the variables in the model are taken in annual basis.

The collecting data and the preparation of the dataset are two important parts in the analysis. As a matter of fact, starting from valid dataset we can run a correct research. Following this consideration we used reliable database such as the OECD database and the Standardised World Income Inequality (SWIID) database.

Even if Gini coefficient is not the only instrument used by researchers to study income inequality, it is the only income inequality measure with available data for our dataset.

One of the main problem, studying the income inequality, is the comparability of the available data among different database. In order to solve this problem, it was developed the SWIID.

As described in Solt (2016), the SWIID aims to unify the overall data from the most important income inequality database, maximising the comparability of available data and increase the availability for many countries.

Indeed the SWIID uses a algorithm to standardise observations collected from the OECD Income Distribution Database, the Socio-Economic Database for Latin America and the Caribbean, Eurostat, the World Bank, national statistical offices around the world, and many other sources. Luxembourg Income Study data serves as the standard. For the purpose of our thesis we adopted the SWIID as database for the Gini coefficient, taking advantage of its properties of international comparability and inclusion of incomes from different sources.

For the macroeconomics variables we followed the paper by Nakajima that, starting from the paper by Coibon et al. (2012), identifies two main general distributive channels of monetary policy.

One is the inflation channel that incorporates the financial segmentation, the portfolio and the savings redistribution channels.

Second is the income channel that incorporates the income composition and the earnings heterogeneity channel.

Inflation channel is identified with prices while income channel with the GDP.

Following the above considerations, we selected as independent variables the real growth GDP¹ and the Consumer Price Index (CPI).²

- GDP_{it} : this measures the annual variation of GDP in the country i at time t , this variable should affect the distributional variable Gini, given that an higher GDP influences the economy, boosting the demand for goods, influencing the investments end employment, improving conditions in general but in particular for the low income households.
- CPI_{it} : this measures the inflation in the country i at time t , this variable should affect the distributional variable Gini, given that for example an increase in inflation

¹is GDP given in constant prices and refers to the volume level of GDP. This indicator is measured in growth rates compared to previous year, OECD database.

²Inflation measured by consumer price index (CPI) is defined as the change in the prices of a basket of goods and services that are typically purchased by specific groups of households. Inflation is measured in terms of the annual growth rate and in index, 2010 base year, OECD database.

transfers wealth from households with nominal assets to those with nominal debt. Thinking that most of low income households hold more debts, the inflation should affect positively Gini coefficient.

Furthermore we added to the model the Unemployment rate (Harmonised Unemployment Rate)³

- U_{it} : this is the unemployment rate in the country i at time t , this variable should affect positively Gini coefficient.

As monetary policy measure, we adopted the shadow interest rate proposed by Xia and Wu as previously mentioned in section 2.2.1.

This instrument is the best choice to capture the overall monetary policy since the MRO's rate is not able to measure the monetary policy after the introduction of unconventional policies.

As previously described, the shadow rate moves in two main directions: when the policy rate remains positive above 0 the rate follows the MRO's rate, at the contrary when the MRO's reaches the Zero Lower Bound the Shadow Interest Rate moves in negative area. With the aim to analyse possible structural breaks in the model, we added a dummy variable ($d2008$) that accounts for the possible impact of the financial crisis.

Furthermore, we include the interaction effects between the dummy $d2008$ and the macroeconomics variables in order to investigate possible changes during the entire sample period. Including the dummy variable and the interaction effect we should obtain better results.

Considering the above variables the model is:

$$G_{it} = \beta_1 GDP_{it} + \beta_2 CPI_{it} + \beta_3 U_{it} + \beta_4 S_rate_t + \beta_5 d2008 + \beta_6 dGDP + \beta_7 dCPI + \beta_8 dU + \alpha_i + \varepsilon_{it}$$

Where:

- G_{it} = net Gini coefficient (post-tax, post-transfer)
- GDP_{it} = real growth Gross Domestic Product.

³Harmonised unemployment rates define the unemployed as people of working age who are without work, are available for work, and have taken specific steps to find work. The uniform application of this definition results in estimates of unemployment rates that are more internationally comparable than estimates based on national definitions of unemployment. This indicator is measured in numbers of unemployed people as a percentage of the labour force and it is seasonally adjusted, OECD database.

- CPI_{it} = Consumer Price Index, inflation is measured in terms of the annual growth rate and in index, 2010 base year.
- U_{it} = Harmonised Unemployment Rate, this indicator is measured in numbers of unemployed people as a percentage of the labour force.
- S_rate_t = the Shadow Interest rate proposed by Wu and Xia for European Central Bank.
- $d2008$ = dummy variable, 1 if Time > 2008, to investigate the impact of financial crisis.
- $dGDP$ = interaction effect between the dummy variable $d2008$ and the macroeconomic variable GDP_{it} .
- $dCPI$ = interaction effect between the dummy variable $d2008$ and the macroeconomic variable CPI_{it} .
- dU = interaction effect between the dummy variable $d2008$ and the macroeconomic variable U_{it} .
- α_i = time-invariant effect.
- ε_{it} = error term.

4.2 Econometric Structure

In line with our dataset we implement a panel data model.

Consistent to the above econometric literature, panel data considers both the cross sectional and time series component, where i denotes the cross section units and t denotes the time series.

The main distinction between the available linear panel data models is that between FE model and RE model.

Starting from the same equation for the model

$$y_{it} = \beta'x_{it} + \alpha_i + \varepsilon_{it}, \quad (4.1)$$

where $\varepsilon_{it} = \alpha_i + v_{it}$

The two models differ in the assumption about α_i . The FE model assumes that the country effect is correlated with the regressors whereas the RE model assumes the uncorrelation, but both of them assumes the uncorrelation between α_i and v_{it} .

Before applying the test to choose between the two mentioned models, we develop test to verify poolability of the data.

The test is applied to the following models:

$$y_{it} = \beta' x_{it} + v_{it}, \quad (4.2)$$

$$y_{it} = \beta' x_{it} + \alpha_i + v_{it}, \quad (4.3)$$

testing if country effect is necessary or not.

Consequently the null hypothesis considers the adoption of OLS model without country effect, whereas the alternative include it.

To apply the test with the software Stata, we develop a regression with the fixed effect (*fe*) option.

The F test with the hypothesis that all $\alpha_i = 0$ allows us to choose between FE or OLS. Rejecting the null hypothesis suggests the the OLS estimates are biased and inconsistent, subjected to a probably omission variables problem.

This test is available even for the RE model, applying the *xttest0* function with the Stata software after the regression with the random effect (*re*) option. Applying the test for RE and FE models, we observe that both of them show the rejection of the null, consequently we include in both of models the country effect α_i .

- Breusch and Pagan Lagrangian Multiplier test for random effects

```
Var(u) = 0
chibar2(01) = 806.02
Prob > chibar2 = 0.0000
```

- F test that all $u_i = 0$, for fixed effects

```
F(10,163) = 415.53
sargan-Hansen statistic 40.222 Chi-sq(7)
Prob > F = 0.0000
```

As previously introduced RE and FE models differ in the assumption of the correlation between the individual specific effect and the regressors.

FE assumes the correlation between the time invariant factor and the regressors. In line

with this consideration, FE model, probably is more appropriate for our dataset as the individual effect α_i (the specific characteristics of countries) appears to be correlated to the other regressors.

To check this intuition in Stata, we perform the *xtoverid* function, applying a test to select the correct model between RE and FE. The test suggests a FE model.

- Test of overidentifying restrictions: fixed vs random effects
 Cross-section time-series model
 sargan-Hansen statistic 40.222 Chi-sq(7)
 P-value = **0.0000**

This test works in the same way of Hausman test under a homoscedasticity condition, whereas the *xtoverid* test is robust to heteroscedasticity.

Including in the model the country effect we obtained the following model:

$$y_{it} = \beta' x_{it} + \varepsilon_{it}, \quad (4.4)$$

where $\varepsilon_{it} = \alpha_i + v_{it}$.

Furthermore to understand if the individual-invariant effect λ_t is not significance for our dataset, we develop a test.

In Stata we apply the *testparm* command after the fixed effect regression adding the individual-invariant term.

Since we accept the null that λ_t are jointly equal to 0, we exclude the individual time effect from our model.

In line to the task of our research we include in the model a dummy variable and the interaction effects between the dummy and macroeconomic variables.

Thus after the regression of fixed-effect model we perform the test to investigate the joint significance of interaction effects.

Since the null is rejected we include in the model the interaction effects.

After these considerations, since the error structure of the basic FE model considers homoscedastic disturbances with the same variances across time and individuals, we check this assumption that can be restrictive in a panel data context.

In the presence of heteroscedasticity we will obtain biased standard errors of the estimates, consequently we should correct the standard errors applying robust option.

In a panel data context the possible heteroscedasticity problem is probable link to the cross section units, the so called groupwise heteroscedasticity, where the variance is the same within cross sectional units and the error structure is heteroscedastic across them.

With the Stata function *xttest3* we test for groupwise heteroscedasticity in fixed effect

regression model.

Rejecting the null the results show the presence of heteroscedasticity.

Furthermore, in order to obtain unbiased estimates of standard error and get efficient results, we have to check the presence of serial correlation in the panel data model, implementing the test proposed by Wooldridge (2002)⁴.

To verify serial correlation in Stata we follow the *xtserial* command by David Drukker, that executes a Wald test.

Since the null hypothesis is no-first order autocorrelation, our data lead to reject the null.

In line with Pesaran (2015) [8], Ignoring cross-sectional dependence of errors can have serious consequences, and the presence of some form of cross-section correlation of errors in panel data applications in economics is likely to be the rule rather than the exception. In Stata the *xttest2* command developed the Breusch-Pagan test of independence in the residuals of FE regression model.

Since the regression with the *fe* option assumes independence in the error, considering a panel data context a possible deviation from independent errors can arise from contemporaneous correlation across cross sectional units.

With the null hypothesis of independence, the test, rejecting the null, suggests the presence of cross sectional dependence.

Following to the above results and considerations, we have to correct the error structure of our model in order to obtain unbiased estimates of standard errors.

For this purpose, we follow the Driscoll and Kraay (1998) estimator.

Driscoll and Kraay developed an estimator which provides standard errors that are consistent and robust to heteroscedasticity and cross section dependence. This estimator is implemented in Stata by Daniel Hoecle, with the *xtscc* command, estimating FE model using Driscoll and Kraay standard errors, the error structure takes into account for correlation between panels, autocorrelation and heteroscedasticity.

Starting from this analysis of a static panel model where the fixed effect model with Driscoll and Kraay estimator appears the best choice for our dataset, we perform further an analysis adding the lagged dependent variable. In order to check if the "history" of our dependent variable is important, we developed a dynamic panel data model. In the static panel data model, the presence of serial correlation is overcome with the adoption of robust standard errors.

But in this way, the information remains in the error term, modifying the error structure. But when is reasonable to consider the lagged dependent variable, supposing the significant relationship between y_{it} and $y_{i,t-1}$, the solution should not be the robust option but specify a dynamic panel model. In this sense we develop a dynamic panel model adding

⁴by taking the first difference, Wooldridge(2002) first estimates the parameters obtaining the residuals, then develops a regression for the residuals on their lags with first differenced variables, testing that the coefficient is equal to 0.5.

Table 4.1:

Command	Option	SE estimates are robust to disturbances being
<code>xtreg</code>	<code>robust</code>	heteroscedastic
<code>xtreg</code>	<code>cluster()</code>	heteroscedastic and autocorrelated
<code>xtscc</code>		heteroscedastic, autocorrelated and cross-sectionally dependent

the lagged value of Gini coefficient.

To do so we use the Stata command `xtlsdvc` proposed by Bruno.

Chapter 5

Results

In line with the selected model, this part shows the results. In order to verify them we perform several robustness checks. The software used for the research is Stata.

5.1 Empirical Results

We tried to identify a correct model for our dataset. It is useful comparing the obtained results looking at the single table 5.1 on the next page. Starting from the preliminary analysis, first we tried to understand which was the better model between pooled OLS, Random Effect and Fixed effect model.

As mentioned in the section 4.2, the first test suggests that pooled OLS model is not good for our dataset, thus the test suggests to use fixed effect.

We developed some tests to identify technical problems as heteroscedasticity, serial correlation and cross section dependence, concluding the presence of both of three conditions. In line with these considerations the final model selected for our interpretations is the number 4, the fixed effect model with Driscoll and Kraay estimator for the standard errors. This model overcomes all the above problems, estimating robust standard errors.

We also perform a dynamic model but we prefer to use the static model for our analysis . The problem is that estimating a dynamic panel model can lead to find a very significance of the lagged dependent variable Gini and a not significance for the other variables.

Nevertheless, a static model can show that the other variables probably are important to explain the relations. From a prediction point of view, probably the dynamic model is more appropriate, but it could reveal us that Gini coefficient "this year" will be high for countries that had higher Gini index in the "previous year".

But in this way we are not able to capture what generated the high Gini index in the past. Therefore a static model may be more useful since we are not interested to the coefficient

Table 5.1: Dependent Variable *Gini coefficient*

<i>Variable</i>	Estimator			
	(1) Pooled OLS	(2) Random Effect	(3) corrected LSDV	(4) Discroll and Kraay (Fe)
G				
L1.			0.9695 *** (0.0259)	
GDP	-0.0254 (0.1313)	0.1012 ** (0.0327)	-0.0211 (0.0115)	0.0981 *** (0.0121)
CPI	1.6168 *** (0.2491)	0.1476* (0.0723)	-0.0354 (0.0216)	0.1166 * (0.0526)
U	0.5438 *** (0.1079)	0.0185 (0.0378)	-0.0106 (0.0127)	0.0018 (0.0491)
S_rate	0.1794 (0.2280)	-0.0962 (0.0506)	0.0354 * (0.0150)	-0.0977 ** (0.0271)
d2008	4.3797 ** (1.5578)	0.1473 (0.0376)	-0.2664 (0.1383)	0.0296 (0.4242)
dGDP	0.0282 (0.1587)	-0.0951 * (0.0376)	0.0242 (0.0128)	-0.0917 *** (0.0165)
dCPI	-1.4821 *** (0.3341)	-0.0882 (0.0870)	0.0610 * (0.0280)	-0.0599 (0.0746)
dU	-0.1433 (0.1208)	0.0311 (0.0329)	0.0272 ** (0.0103)	0.0391 (0.0489)
cons	20.8693 *** (1.2960)	28.9923 *** (0.6894)		29.1900 *** (0.3938)

legend: * p<0.05; ** p<0.01; *** p<0.001

of the lagged dependent variable. Furthermore, the small T dimension of our dataset leads to exclude the adoption of dynamic panel.

Observing the table 5.1 on the facing page, some variables are not significant:

- U_{it} : unemployment rate is not significant even if we should expect a significance positive effect. For our empirical data, the rise of unemployment rate does not lead to an increase in the Gini index.

The significant variables are the following:

- GDP_{it} : the annual growth rate of GDP is significant at 99,99% confidence level. In particular the increase of one unit of GDP growth leads to to an increase in the Gini coefficient of 0.098, thus income inequality. This positive effect is the opposite of what we supposed, actually a positive GDP growth generally indicates an improvement in the economic conditions in the country.
- CPI_{it} : inflation is significant at 95% confidence level. The coefficient shows a positive relation of 0.1166, supporting our previous considerations on the expected effect.
- S_rate_t : shadow interest rate that identifies the ECB's monetary policy stance is significant at 99% confidence level. The coefficient reveals a negative effect of -0.0977 on the Gini coefficient. An increase in the shadow rate leads to a decrease of Gini index. An increase in the shadow rate is associated to a restrictive monetary policy while a decrease in the shadow rate correspond to an expansive monetary policy.
- $dGDP$: the interaction effect between $d2008$ and GDP is significant. Therefore there is an effect of financial crisis on the GDP growth variable.

Therefore by analysing the results for the entire period 1999-2015, the significant correlation between the shadow interest rate and the Gini coefficient shows that there is an effect of ECB's monetary policy on income inequality.

The effect of the coefficient (-0.0977) exhibits a negative effect.

An increase (decrease) in the shadow rate leads to a decrease (increase) in Gini coefficient. From these considerations a restrictive (accommodative) monetary policy associated to an increase (decrease) in the shadow rate lead to an decrease (increase) in income inequality.

5.2 Robustness

In order to support the previous results, we developed two robustness checks. First, we performed the same analysis excluding the first 3 years from 1999 to 2002.

Although the ECB formally started its operations in 1999, consolidating the single monetary policy, there was a transition phase of three years leading to the replacement of the national currency by euro banknotes and coins. Greece consolidates the third stage of the European monetary union on 1 January 2001 and on 1 January 2002, the euro banknotes are introduced.

In order to these considerations, given that the first three years, 1999-2001 could affect results, we developed a robustness test to check this possible effect.

Looking at table 5.2 on the next page, we can observe that the results are in line with the baseline model.

There are some variables that become significant but considering the sign, the significance and comparing to the significance variables in the baseline model, we can conclude that they deviate from those of baseline model but not in a robust way. In particular for the variable S_rate_t .

Second, in order to support the results we decomposed the sample in two subsamples. The first considers the period 1999-2008 and the second the period 2009-2015. We developed this test to identify possible variation of the coefficient taking into account the period before and after the implementation of unconventional monetary policies.

The table 5.3 on page 40 shows the results, some of them appear contradictory. For the GDP the results support those of the baseline model. Actually the fact that the variable is positive significant only in the second period support the positive effect of GDP and the interaction effect $dGDP$ in the baseline model.

For the CPI, the results appear in line for significance and sign but only in the second period.

The shadow interest rate remain negatively significant but only in second period. This supports the results of the baseline model but it indicates that the effect is significance after the financial crisis with the implementation of unconventional monetary policies.

Table 5.2: Robustness check: sample without 1999-2001

<i>Variable</i>	Estimator: Driscoll and Kraay (Fe)	
	Baseline sample	Without 1999-2001
GDP	0.0981 *** (0.0121)	0.0670 * (0.0249)
CPI	0.1166 * (0.0526)	0.0687 * (0.0311)
U	0.0018 (0.0491)	-0.0963 * (0.0354)
S_rate	-0.0977 ** (0.0271)	-0.0535 ** (0.0151)
d2008	0.0296 (0.4242)	-0.9053 *** (0.1772)
dGDP	-0.0917 *** (0.0165)	-0.0509 (0.0262)
dCPI	-0.0599 (0.0746)	-0.0238 (0.0476)
dU	0.0391 (0.0489)	0.1472 *** (0.0276)
cons	29.1900 *** (0.3938)	30.0589 *** (0.2468)

legend: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 5.3: Robustness check: Subsample 1999-2008 and Subsample 2009-2015

<i>Variable</i>	Estimator: Driscoll and Kraay (Fe)		
	Baseline sample	Subsample 1999-2008	Subsample 2009-2015
GDP	0.0981 *** (0.0121)	0.0865 (0.0456)	0.0068 ** (0.0014)
CPI	0.1166 * (0.0526)	0.0668 (0.0414)	0.0283 * (0.0081)
U	0.0018 (0.0471)	0.1299 * (0.0354)	0.0319 ** (0.0060)
S_rate	-0.0977 ** (0.0271)	-0.1142 (0.0634)	-0.0660 * (0.0180)
d2008	0.0296 (0.4242)		
dGDP	-0.0917 *** (0.0165)		
dCPI	-0.599 (0.0746)		
dU	0.0391 (0.0489)		
cons	29.1900 *** (0.3938)	28.4314 *** (0.4086)	29.3552 *** (0.0775)

legend: * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Chapter 6

Conclusions

Looking at the trend of income inequality across developed countries in the past four decades, we observe a clear increase.

Consequently, the research largely analysed the possible economic and financial implications of this trend.

Only recently, (conventional and unconventional) monetary policy has been put under scrutiny, with the goal of ascertain whether and how it plays some role in the increasing income inequality.

This thesis contributes to the strand of research analysing the effect of ECB's monetary policy on income inequality, measured by Gini index.

In particular, this analysis improves the existing literature in three ways: first, we employed a panel data model, using a panel of 11 EMU countries instead of just one for the period from 1999 to 2015; secondly we adopted the Shadow Interest rate proposed by Wu and Xia as measure of the entire monetary policy (conventional and unconventional); third, while research has only focused on the Federal Reserve or Bank of Japan, we are the first to explore the topic for the Euro area.

The empirical part of the thesis discusses the selection of the correct model for our dataset. After testing all possible models, we decided to implement a fixed effect model with Driscoll-Kraay standard errors. In line with this decision, the results suggest a negative effect of Shadow Interest rate, that measures the ECB's monetary policy stance, on the Gini coefficient.

As described in Coibon et al. (2012), there are some transmission channels through which monetary policy affects income distribution. They differently influence the low and high income households.

During the expansionary monetary policy, the income composition, the financial segmentation, and the portfolio channels could lead to better conditions for high income households improving income inequality.

As a matter of fact since high income households tend to hold more securities, be more

related to financial markets, and rely more on financial earnings, they might gain more from an expansionary monetary policy that usually affects more the price of assets.

Furthermore, one could affirm that the distributive effects of monetary policy are balanced in the long run, declaring that expansionary policy during an economic downturn faces the opposite effect during a restrictive monetary policy. Nevertheless it appears restrictive considering business cycles symmetric.

As supported by Saiki and Frost (2014) in the analysis for Japan, in particular the portfolio channel can have large effect even in the US, UK and in the Euro area, where there is a large concentration of savings in equities and bonds held by households. This could be a starting point for a further research.

Chapter 7

Appendixes

7.1 Appendix A

We performed some tests in order to identify possible problems of our model:

- The test proposed by Wooldridge (1992) develops a regression of the residuals in first differences. To do this in Stata we performed the *xtserial* command. It applies a Wald test, where the null hypothesis is no first order autocorrelation. Based on our dataset the test rejects the null hypothesis.

```
Wooldridge test for autocorrelation in panel data
```

```
H0: no first-order autocorrelation
```

```
F(1,10) = 1113.518
```

```
Prob > F = 0.0000
```

- The Stata command *xttest3* performs a Modified Wald test for groupwise heteroscedasticity in the residuals in fixed effect regression model. The null hypothesis is homoscedasticity and based on our data the test rejects the null.

```
Modified Wald test for groupwise heteroscedasticity in fixed effect regression  
model
```

```
H0:  $\sigma(i)^2 = \sigma^2$  for all  $i$ 
```

```
chi2 (11) = 916.51
```

```
Prob > chi2 = 0.0000
```

- In Stata the *xttest2* command developed the Breusch-Pagan test for cross-sectional independence in the residuals of FE regression model. The null hypothesis is the

cross-sectional independence and based on the our dataset the test rejects the null.

Breusch-Pagan LM test of independence $\chi^2(55) = 360.906$

Prob = **0.0000**

7.2 Appendix B

Variable	Definition	Frequency	Source
G	Net Gini coefficient (post-tax, post-transfer)	Annual	SWIID
GDP	Real GDP growth rate, %	Annual	OECD
CPI	Consumer Price Index, %	Annual	OECD
U	Harmonised Unemployment Rate, %	Annual	OECD
S_rate	The shadow ECB interest rate	Annual	Wu and Xia (2017)
d2008	Pre and post financial crisis	Annual	Calculated
dGDP	Interaction effect with GDP	Annual	Calculated
dCPI	Interaction effect with CPI	Annual	Calculated
dU	Interaction effect with U	Annual	Calculated

7.3 Appendix C

In order to exclude from the our model the individual invariant term λ_t we performed the test to exploit the significance of that variable. In Stata we apply the *testparm* command after the a fixed effect regression adding the individual-invariant term. Since we accept the null that λ_t are equal to 0, we exclude the individual time effect from our model.

- Testparm i.Time
 - (1) 2000.Time = 0
 - (2) 2000.Time = 0
 - (3) 2000.Time = 0

```

. xtreg G GDP U CPI S_rate d2008 dGDP dU dCPI i.Time, fe
note: d2008 omitted because of collinearity
note: 2015.Time omitted because of collinearity

Fixed-effects (within) regression              Number of obs   =   182
Group variable:  countrynum                    Number of groups =    11

R-sq:  within = 0.2228                        Obs per group:  min =    16
        between = 0.2490                       avg             =   16.5
        overall = 0.1411                       max             =    17

                                                F(22,149)      =    1.94
corr(u_i, Xb) = 0.2877                        Prob > F       =   0.0109

```

G	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
GDP	.1435535	.0397206	3.61	0.000	.065065	.222042
U	.0192351	.0378403	0.51	0.612	-.0555378	.0940081
CPI	.0970967	.0860227	1.13	0.261	-.0728853	.2670786
S_rate	-.1291975	.0875534	-1.48	0.142	-.3022041	.0438091
d2008	0	(omitted)				
dGDP	-.1227203	.0434614	-2.82	0.005	-.2086005	-.0368401
dU	.0322733	.0323647	1.00	0.320	-.0316797	.0962263
dCPI	-.0051128	.1128474	-0.05	0.964	-.2281008	.2178752
Time						
2000	.1108828	.320345	0.35	0.730	-.5221232	.7438888
2001	.205579	.28717	0.72	0.475	-.3618728	.7730308
2002	.3261376	.2658574	1.23	0.222	-.1992002	.8514754
2003	.350302	.2491576	1.41	0.162	-.1420366	.8426406
2004	.2212434	.2300222	0.96	0.338	-.2332835	.6757703
2005	.3093286	.2406396	1.29	0.201	-.1661785	.7848357
2006	.2654303	.2592096	1.02	0.307	-.2467713	.7776319
2007	.3857824	.2927223	1.32	0.190	-.1926407	.9642055
2008	.4486921	.3165262	1.42	0.158	-.1767677	1.074152
2009	.4323867	.3180998	1.36	0.176	-.1961828	1.060956
2010	.2597205	.3174763	0.82	0.415	-.3676168	.8870578
2011	.0970636	.3474727	0.28	0.780	-.5895471	.7836743
2012	.1522064	.3287945	0.46	0.644	-.4974958	.8019087
2013	.3880806	.2855642	1.36	0.176	-.1761981	.9523593
2014	.1351347	.2803597	0.48	0.631	-.4188598	.6891292
2015	0	(omitted)				
_cons	28.81274	.3431859	83.96	0.000	28.1346	29.49088
sigma_u	3.3777253					
sigma_e	.5447443					
rho	.97464958	(fraction of variance due to u_i)				

F test that all u_i=0: F(10, 149) = 364.04 Prob > F = 0.0000

Figure 7.1: Fixed effect estimation with individual-invariant variables

```
(4) 2000.Time = 0
(5) 2000.Time = 0
(6) 2000.Time = 0
(7) 2000.Time = 0
(8) 2000.Time = 0
(9) 2000.Time = 0
(10) 2000.Time = 0
(11) 2000.Time = 0
(12) 2000.Time = 0
(13) 2000.Time = 0
(14) 2000.Time = 0
(15) 2000.Time = 0
```

$F(15,149) = 0.42$

Prob > F = **0.9702**

Furthermore after the regression of fixed-effect model we performed the test to investigate the joint significance of interaction effects. Since the null is rejected we conclude to include the interaction effects into the model.

- Testparm d2008 dGDP dU dCPI

```
(1) d2008 = 0
(2) dGDP = 0
(3) dU = 0
(4) dCPI = 0
```

$F(4,16) = 14.40$

Prob > F = **0.0000**

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