Erasmus School of Economics

Master thesis proposal

MSc. Economics & Business: International Economics

The Effect of Unconventional Monetary Policy on Income Inequality: The U.S. Case

Author:
Konstantinos Andreou

Supervisor:
Prof. Agnieszka Markiewicz

Abstract

This paper explores the distributional effect of unconventional monetary policy on income inequality in the United States. Using vector autoregression or vector error correction models and quarterly measures of inequality, we examine whether an increase in the Fed's balance sheet had an impact on total before-tax income and labor earnings. Our findings indicate that unconventional monetary policy worsens labor earning distribution with the result being significant and consistent with different measures of monetary easing and income inequality variables. In contrast, the impact on total income distribution found to be ambiguous and inconsistent between different specifications. We also find evidence for the existence of the income composition channel, but the quality and reliability of the wealth data on CEX do not allow us to decompose the effect of the QE on the total before-tax income and labor income.

Keywords: income inequality, quantitative easing, unconventional monetary policy
JEL codes: D30, D31, E52, E58, E65

September 13, 2018

Contents

List of Tables

List of Figures

List of Abbreviations

AIC	Akaike's information criterion
ADF	Augmented Dickey-Fuller
CEX	Consumer Expenditure Survey
CPI	Consumer Price Index
Fed	Federal Reserve Bank
FPE	Final prediction error
FRED	FRED, Federal Reserve Bank of St. Louis
IMF	International Monetary Fund
IRF	Impluse Response Function
KPSS	Kwiatkowski–Phillips–Schmidt–Shin
PCE	Personal Consumption Expenditures
PP	Phillips–Perron
QE	Quantitative Easing
QoQ	Quarter-on-Quarter
SIC	Schwarz Information Criterion
SCF	Survey of Consumer Finances
VAR	Vector Autoregression
VECM	Vector Error Correction model
YoY	Year-over-Year

1 Introduction

The 2007-09 global financial crisis led central banks of developed countries to an unprecedented pace of monetary policy accommodation. Beyond the cut of short-term interest rates to ultra-low levels, central banks resorted to an unconventional monetary policy known as Quantitative Easing (QE) to prop up the economy. In particular, they conducted large-scale asset purchases to expand the money supply and inject liquidity into the economy.

The combination of the unconventional monetary policy as a response to combat the Great Recession and evidence of growing inequality in developed countries has brought the distributional consequences of monetary policy into the spotlight. While traditionally income distribution forces considered to be of secondary significance, upon the recent developments more central bankers pay closer attention to this matter. Some noteworthy examples are the following. The ECB's president Mario Draghi (2015) stated in Camdessus lecture at International Monetary Fund (IMF) on May 14th, 2015: *"The use of these 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".* Furthermore, the former president of the Federal Reserve Bank (Fed) Ben Bernanke (2015) on his article at Brookings Institute highlighted the imperative need for more research, as he stated, *"to untangle and measure the many channels through which these effects are transmitted".* On the same line were comments of former Fed Chair Janet Yellen (2014) at the conference on Economic Opportunity and Inequality which was organized by the Federal Reserve Bank of Boston on October 17, 2014.

However, even-though many monetary policy officials appear to pay close attention to the distributive impact of the QE policies, the empirical literature is still at infancy with a small yet growing amount of contributions. One of the main reasons is the difficulty in obtaining high-frequency inequality data since most of the available sources provide data at best on an annual basis. In order to tackle this problem, and following Coibion, Gorodnichenko, Kueng, and Silvia (2017), this paper employs household survey data from the Consumer Expenditure Survey (CEX) of the U.S. Bureau of Labor Statistics to construct measures of inequality for total before-tax income and labor earnings on a quarterly basis.

Accordingly, this enables our research to provide insights on the unintended distributional consequences of the unconventional monetary policy followed by the Fed in the U.S. More specifically, we aim to answer whether an increase in the Fed's balance sheet has a disequalizing impact on income inequality using a Vector Autoregression (VAR) model or Vector Error Correction model (VECM). Since the last phase of central bank's asset purchase program ended in October 2014, we believe that the range of our data (2003Q1-2016Q4) suffices to capture most of the primary and lagged effects. Indeed, it should be noted that it is not completely possible to disentangle the impact of the ultra-low interest rates and the QE policy.

Overall, our findings indicate that unconventional monetary policy worsens labor earning distribution with the result being significant and consistent with different measures of monetary easing and income inequality variables. Thus, we provide evidence that QE leads to higher inequality through the earnings heterogeneity channel. In contrast, the impact on total income distribution found to be ambiguous and inconsistent between different specifications. We also find evidence for the existence of the income composition channel, but the quality and reliability of the wealth data on CEX do not allow us to decompose the effect of the QE on the total before-tax income and labor income.

The rest of the paper is organized as follows. Section 2 provides an elaborate review of the empirical literature regarding the impact of monetary policy on inequality and sets our research question. Section 3 describes the data of the empirical analysis and explains the construction of our inequality variables. Section 4 summarizes the methodological process for analyzing the impact of unconventional monetary policy on income inequality. Section 5 introduces the results of our analysis an reports robustness checks. Finally, Section 6 concludes.

2 Literature review

The empirical examination of the redistributive impact of the unconventional monetary policy on inequality is still quite thin in the academic literature with a small yet growing amount of papers contributing to this particular research area. Despite that, and as it has already been mentioned, the topic has become part of the public debate with multiple monetary policy officials to pay attention to the matter. In contrast, the effect of inflation on poverty and inequality is somewhat older and better analyzed being influenced by the seminal work of Kuznets (1955) on economic growth and income inequality. Nevertheless, since inflation is one of the policy targets of the monetary policy authorities globally, this literature review focuses on papers related to both issues.

2.1 Inflation and inequality

Starting the analysis of the relationship between inflation and income inequality, there is multiple empirical evidence which, mostly, support the idea that inflation and income inequality are positively correlated.

Bulir (2001) provides evidence that lower inflation improves income equality regardless of the initial level of GDP per capita by using cross-country data from 75 countries and a traditional Kuznets model. Furthermore, his analysis suggests that the positive effect of price stabilization on income distribution is non-linear and, therefore, the marginal effect of inflation on inequality lowers as inflation moves from hyperinflation towards lower levels. However, the effect of inflation on income equality is revealed after a number of periods.

Li and Zou (2002) employ cross-country panel data consisting of 46 countries in order to evaluate the impact of inflation on income distribution. Authors' results suggest that inflation negatively affects economic growth and income inequality by benefiting the wealthier people and reducing the income of the other classes disproportionately. Additionally, Erosa and Ventura (2002) analyze households' transaction patterns and portfolio holdings for the U.S. and suggest that the cost of inflation is unevenly distributed. Hence, inflation has severe distributional effects as it acts similar to a regressive consumption tax. Moreover, accessing polling data for 38 countries, Easterly and Fischer (2001) find that inflation and variables associated with the well-being of the poor are negatively correlated. The researchers also show that the poor are more likely than the rich to classify inflation level as a top national priority.

Observing a strong positive cross-country correlation between income inequality and the average inflation rate in the post-war period, Albanesi (2007) argues that the identified relationship is the outcome of the distribution conflict that determines fiscal policy. In this seminal paper, the author states that low-income households hold a higher portion of their total expenditures in cash and, beyond that, wealthier households influence the implemented fiscal policies more. Thus, the government uses seigniorage as a financing instrument rather tax rate increases which results in a higher loss for the poor due to the higher inflation rate.

Ultimately, analyzing the relationship between inflation and income inequality in 13 European countries during the period 2000 to 2009, Thalassinos, Ugurlu, and Muratoglu (2012) provide supportive results for a positive relationship.

Contrarily to the findings of the previous papers, Doepke and Schneider (2006) quantitatively assess the impact of inflation on redistribution of the nominal wealth through changes in the nominal value of assets for the U.S. and identify wealthy household as the main losers of inflation. Accordingly, inflation and income inequality are negatively related. In particular, the authors advocate that young, middle-class families with fixed-rate debt benefit the most from inflation as the real value of their debt decreases.

2.2 Conventional monetary policy and inequality

Early work on the impact of monetary policy shock on inequality is that of Romer and Romer (1999). The authors use a time series analysis for the U.S. and a sample of 66 cross-country data to evaluate the distributional impact of monetary policy. In the former case, they find that expansionary policy decreases inequality in the short-run while in the latter, their results suggest that contractionary monetary policy is beneficial for the poor in the long-run. However, despite the contradictory results, Romer and Romer (1999) conclude that the stable aggregate demand and low inflation are most likely to benefit the well-being of the poor since the effects of monetary policy shocks are inherently temporary.

Galli and van der Hoeven (2001) analyze data of 16 OECD countries, including the U.S., and find a U-shape association between income inequality and inflation which depends on the initial level of the latter. In particular, the authors argue that in high inflation countries tight monetary policy improves equality while, in contrast, the same monetary policy can deteriorate inequality when the initial level of inflation is low. Auda (2010) performs the same methodology in an extended sample size and reaches a similar conclusion.

Employing a VAR model for the U.S. from 1984 to 2003, Galbraith, Giovannoni, and Russo (2007) show that contractionary monetary policy raises earnings inequality in the manufacturing sector by influencing the term structure of interest rates. Subsequently, using data for the U.S. over the period 1980-2008, Coibion et al. (2017) find that tight monetary policy systematically raises inequality in consumption, total expenditures, labor earnings and total income. More importantly, though, the researchers document five different channels through which monetary policy shocks impact economic inequality (See Section 2.4).

Doepke, Schneider, and Selezneva (2015) quantitatively evaluate the redistributive implications of monetary policy on the U.S. households with a life cycle model also considering house price adjustments in response to demand changes. Their results indicate that tight monetary policy contributes to income redistribution by benefiting leveraged middle-class, middle-aged households and hurting wealthy retirees. Furthermore, the authors highlight the existence of heterogeneous welfare effects when nominal interest rate increases. Indeed, the asymmetric impact of inflation on borrowers and lenders is well documented in the literature (Erosa & Ventura, 2002; Doepke & Schneider, 2006). Finally, Doepke et al.

(2015) find the existence of persistent effects of monetary policy which disseminate through wealth distribution.

Brunnermeier and Sannikov (2012) argue that monetary policy redistributes the wealth across economic agents through changes in asset prices with the asymmetric level of asset holdings across households constituting the main channel. Thus, the appropriate monetary policy can increase the overall wealth level by mitigating debt overhang distortions that destabilize the economy, increase endogenous risk and hinder growth. Moreover, the researchers identify short-term interest rates as a second channel that leads to wealth redistribution mainly by altering the cost of borrowing.

Besides, Mumtaz and Theophilopoulou (2017) study the effect of monetary policy shocks on income and earnings inequality in the UK from 1969 until 2012. Employing a mixed frequency structural VAR model, the authors advocate that tight monetary policy shocks are associated with higher levels of consumption, earning and income inequality. Finally, Furceri, Loungani, and Zdzienicka (2018) investigate the same relationship with a panel of 32 advanced and emerging economies over the period 1990–2013 and provide consistent results.

Lastly, Gornemann, Kuester, and Nakajima (2016) build a New Keynesian DSGE model with heterogeneous-agents, incomplete asset-markets, heterogeneous preferences, frictional labor market and price stickiness to access the distributional consequences of conventional monetary policy. Authors' main finding indicates that most of the households prefer sizable stabilization of unemployment by the monetary authorities even when this is associated with departure from price stability. The reason is that monetary policy which focuses on unemployment acts like an insurance in consumption lowering the amount of precautionary saving and, therefore, asset prices.

2.3 Unconventional monetary policy and inequality

The first contribution to the effect of unconventional monetary policy on income inequality comes from the Bank of England (2012). The Treasury Committee conducted a partial equilibrium analysis over the period 2009-2012 assessing the impact of the QE on savers and pensioners. Regarding the former, the Committee acknowledges the fact that asset purchases benefited disproportionally the wealthiest 5% of the British households which holds about 40% of their wealth on investments outside pension funds. Bank of England (2012) refers to a transmission channel similar to those described on Brunnermeier and Sannikov (2012) and Doepke et al. (2015). Concerning the latter, they argue that asset purchases from Bank of England affected negatively only households participating in underfunded defined benefit pension schemes. However, the report highlights the paramount role of the program for the UK economy in the absence of which the broad majority of the population would be worsened.

Another essential contribution examines the impact of unconventional monetary policy on inequality for Japan. Saiki and Frost (2014) use household survey data and a VAR model to estimate the impact of Bank of Japan's QE over the period 2008:Q3-2014Q1.

Their results provide evidence for positive economic growth and widening income inequality during the periods of unconventional monetary policy with more aggressive quantitative easing policies to be linked with more unequal income distribution. Hence, less equality appears to be a side effect of the unconventionally monetary policy. Besides, the researchers consider the portfolio channel as the primary underlying mechanism stating that an increase in asset prices benefits wealthier households more than the others as they have more substantial investments in securities and capital income.

Domanski, Scatigna, and Zabai (2016) explore the potential effect of unconventional monetary policies around the globe on households' wealth equality in France, Germany, Italy, Spain, the UK and the U.S. Their partial equilibrium analysis identify rising equity prices as a key driver behind the increasing wealth inequality since the Great Recession. In contrast, the effect of the rising bond prices and the lower interest rate were found to be negligible. Nonetheless, their analysis has important caveats. Among others, their wealth measures do not take into account the value of human capital and pension fund schemes or the impact on unemployment and growth. However, assessing the distributional consequences of bond and equity for the Euro Area, Adam and Tzamourani (2016) results confirm the findings above.

Concerning the effect of the QE in the case of the U.S., Montecino and Epstein (2015) analyze the development of income by quantile in the pre-QE and post-QE period using data from the Federal Reserve's Tri-Annual Survey of Consumer Finances. More specifically, the authors apply recentered influence function regressions with Oaxaca-Blinder decomposition technique and investigate three channels through which unconventional monetary policy affects income distribution: (1) the asset appreciation and return channel, (2) the employment channel, and (3) the mortgage refinancing channel. Their findings indicate a moderate dis-equalizing impact of the QE as the adverse effect of equity price appreciation outweighed the beneficial impact of employment and mortgage refinancing. Surprisingly, authors' assessment yield minor distributional impact from bond price appreciation. Another report that focuses on the U.S. is that of Dobbs, Lund, Koller, and Shwayder (2013) which, indeed, provides evidence for a negative impact of the unconventional monetary policy and the ultra-low interest rates. The authors advocate that pension funds, life insurance companies and households realized lower net interest income because their balance sheet consists of substantially more interest-bearing assets than liabilities.

Nevertheless, the adverse effect of non-conventional monetary policy on income distribution is not consistent in the literature. O'Farrell, Rawdanowicz, and Inaba (2016) find a negligible impact of unconventional monetary policy on income and wealth distribution in a number of advanced economies with the composition and the size of households' balance sheet to play a more crucial role. Moreover, Casiraghi, Gaiotti, Rodano, and Secchi (2018) exploit a micro dataset on income and wealth of Italian households' to investigate the distributional effects of the ECB's unconventional monetary policy. Their results also show a negligible effect on wealth and income distribution since the negative impact of higher asset prices and the positive effect of higher employment and improved economic activity offset each other. Finally, Deutsche Bundesbank (2016) economists after reviewing many of the previously mentioned papers and conducting their analysis, argue that, if anything, unconventional monetary measures lowered income inequality while the ramification on wealth distribution is still unclear.

2.4 Linking monetary policy and inequality

The different impacts of monetary policy on income distribution arise mainly due to the evaluation of various distributional channels in the literature. Overall, Coibion et al. (2017) distinguish five transmission channels whereby monetary policy can affect income inequality. The first three channels described below may have a disequalizing effect on income distribution in response to expansionary monetary policy actions while the last two tend to reduce inequality.

First, the *income composition channel* refers to the heterogeneity of households' primary source of income. Although most households depend mainly on labor income, other households also receive income from capital. Hence, considering that wealthier individuals tend to get a higher proportion of their income from capital profits if expansionary monetary shocks increase capital gains disproportionally to labor income, then monetary policy will contribute to income inequality via this channel. Second, the *financial segmentation channel* describes the reallocation of income towards agents participating in the financial markets because money supply changes benefit them before non-participants. However, the former group tends to have higher income and consumption compared to the latter and, therefore, expansionary monetary policy shocks can lead to consumption inequality. Another channel related to the participation of agents in the financial markets is the *portfolio channel*. Since high-income households tend to hold lower amounts of currency compared to low-income, inflationary policies will result in a disequalizing redistribution. Penultimately, the *savings redistribution channel* states that a contractionary monetary policy tends to reduce consumption inequality since it hurts savers and benefits borrowers. Thus, when inflation lowers or interest rates increase the former group suffers losses and the latter group realizes gains leading to a more unequal consumption. An empirical assessment for this transmission channel has been provided by Doepke and Schneider (2006). Lastly, the *earnings heterogeneity channel* refers to the idea that the response of labor earnings to monetary policy shocks may differ for low-income and high-income households.

2.5 Research question

All things considered, it becomes clear that the empirical evidence regarding the effect of conventional and, especially, unconventional monetary policy on inequality are still at infancy and inconclusive. Therefore, this thesis aims to contribute to the literature by analyzing the distributional impact of the Federal Reserve's unconventional monetary policy on income inequality based on household survey data. In essence, the hypothesis that we aim to investigate is the following: *Does an increase in assets held by the Fed has an impact on income inequality?*

3 Data description

Before introducing the variables of our model, we briefly discuss the methodology and the sample period of our analysis. In order to investigate the formulated hypothesis, we employ a VAR model or VECM using quarterly data for the U.S. over the period 2003:Q1 to 2016:Q4. The first observation of the sample is based on the quarter that our main variable to capture unconventional monetary policy is available. Although the third phase of the QE ended in October 2014, the last observation of our sample size is extended until 2016:Q4 to capture any possible lagged effects on income inequality.

3.1 Measuring inequality

There are multiple databases providing annual versions of widely used inequality measures such as the Gini coefficients and income percentile ratios. However, the fundamental empirical challenge with regards to the effect of unconventional monetary policy on income distribution is to obtain inequality data of a higher frequency. For this reason, we follow Coibion et al. (2017) and construct quarterly measures of inequality (see Section 3.1.1) using data from the CEX of the U.S. Bureau of Labor Statistics.

The CEX is a nationwide comprehensive survey which provides information on consumers' spending and income in the U.S. More specifically, we employ income data from FMLI files of the quarterly Interview Survey to obtain before-tax total income and labor earnings data. These variables are denoted in the database as *fincbtxm* and *fsalarym*, respectively (Bureau of Labor Statistics, 2017). The benefit of using labor earnings to calculate income inequality is the enhanced quality and precision of the data compared to those for total income. However, relying only on labor earning overlooks other important sources of income such as for instance, financial income and transfers. As a result, we construct measures of inequality for both total income and labor earnings which means that we can directly analyze the income composition and earning heterogeneity transmission channels. Nonetheless, we cannot quantify the impact between the other channels as the survey does not provide high quality and reliable wealth data.

3.1.1 Construction of inequality measures

For the purpose of our analysis, we construct two different income inequality variables: Gini coefficients of the variables in levels and 90th/10th percentile ratios of the logarithmically transformed variables. The Gini coefficient compares inequality across the whole income distribution and it is one of the most widely used measures of inequality. Thus, we consider it as the basic inequality variable of our analysis. To reduce the sensitivity of our inequality measure to outliers, we also use the 90th/10th percentile ratio of the logarithmically transformed variables to investigate the effect of unconventional monetary policy on income inequality between the top and the bottom. However, this requires to exclude all observations equal to zero.

Table 1 presents the descriptive statistics of the constructed inequality variables and

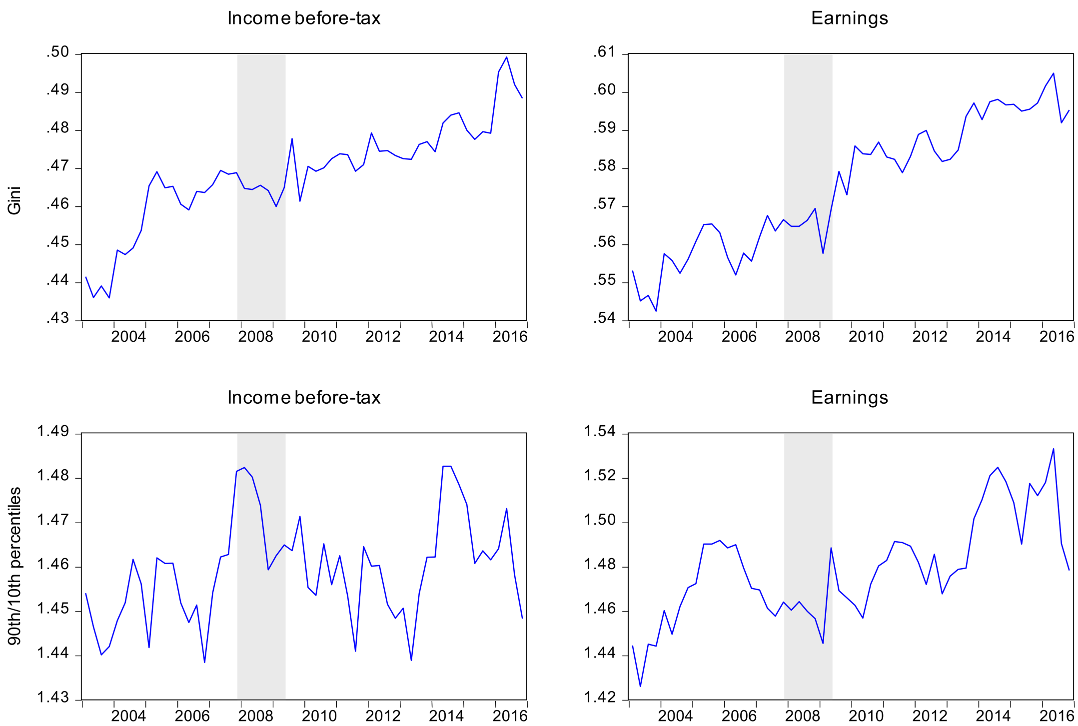
Figure 1 displays the evolution over the period of our analysis. We see that the average value of both measures of inequality is greater for labor earning rather than total income inequality. The reason is that total income also includes other income-dependent sources of income that reduce inequality such as unemployment benefits, cash from scholarships and income from job training grants. Our estimates compare to those obtained from Coibion et al. (2017) who find total and labor income Gini coefficients on the ranges 0.46-0.49 and 0.55-0.58 over the period 2005 to 2010, respectively. Additionally, the U.S. Census Bureau total before-tax income Gini coefficient of 0.48 in 2014 is in line with our estimation.

Table 1: Descriptive statistics of inequality variables

Inequality Variables	Model Name	Mean	Min	Max	St.Dev.
Gini coefficient					
Income Inequality	Gini_Income	0.47	0.44	0.50	0.01
Earnings Inequality	Gini_Earnings	0.58	0.54	0.60	0.02
90th/10th percentile					
Income Inequality	Ratio_Income	1.46	1.44	1.48	0.01
Earnings Inequality	Ratio_Earnings	1.48	1.43	1.53	0.02

Source: Authors' calculations based on data from CEX of the U.S. Bureau of Labor Statistics

Figure 1: Inequality in total income and labor earnings in the U.S.



Note: The gray shaded areas indicate the Great Recession in the U.S economy which officially started in December 2007 and lasted until June 2009.

Source: The CEX of the U.S. Bureau of Labor Statistics

3.1.2 Inequality data issues

Although the use of CEX data solves the frequency problem of obtaining quarterly inequality variables, there are two considerable limitations. First, and most importantly, the CEX excludes the top 1% of the income distribution which in the period 2009-2015 recorded a real income growth of 37.4% against an average of 13% and a rise of 7.6% at the bottom 99% of the income distribution (Saez, 2015). Accordingly, Lansing and Markiewicz (2016) present data that the share of the top quantile has been remarkably increased over the period 1970 to 2014 in the U.S. Therefore, the constructed inequality measures could underestimate the distributional impact of monetary policy shocks. Second, since we use survey data, the constructed measures of income inequality are of lower quality compared to those from administrative data due to the measurement errors (Groves, 2004).

Ideally, we would like to employ data from the triennial Survey of Consumer Finances (SCF) to construct our inequality variables as the survey provides an unparalleled amount of high-quality data with regards to a household's balance sheet. Therefore, we would be able to capture the effect of multiple channels through which the unconventional monetary policy shocks might have affected income distribution. Also, the SCF gathers demographic information of the interviewed families and variables related to labor market being useful to identify the impact on inequality between different sub-groups. However, for the purpose of our analysis, we are unable to use those data as the survey withholds a number of variables to protect the anonymity of the respondents. Most importantly, data related to the interview dates within the three year collection period are not available implying that we cannot construct quarterly inequality indexes.

3.2 Model variables

After explaining the construction of our inequality measures, the next step is to select the rest of endogenous variables entering into the model. First, to capture overall economic activity, we use the real GDP because it excludes inflation and exchange rate distortions. The data for the real GDP are obtained from the FRED, Federal Reserve Bank of St. Louis (FRED) and we refer to this variable in our paper as *RGDP*. In the empirical part of our research we transform RGDP logarithmically meaning that if we take the first difference, it can be interpreted as Quarter-on-Quarter (QoQ) real GDP growth.

Second, we have to choose a variable that captures the price level of goods and services in the economy. In the U.S., the most widely used measures of inflation are the Consumer Price Index (CPI) and the Personal Consumption Expenditures (PCE) index. Markedly, the two measures follow similar trends but, for reasons described at McCully, Moyer, and Stewart (2007), are definitely not identical (see Appendix Figure A.1). Briefly, the differences of the two inflation measures arise from the differences in the scope of the expenditures, the weights used in different categories and on the way that the changes in the basket are treated. Overall, CPI tends to yield higher inflation estimates compared to PCE. Furthermore, both CPI and PCE index are released in two versions. The first version is called "headline" and incorporates the price of all items in the basket of the index while the second is known as "core" and excludes volatile food and energy constituents. Since the Federal Reserve uses the annual change in the PCE index as a benchmark, PCE is preferred over CPI (Federal Reserve, 2012). Furthermore, as Fed's Monetary Policy Report presents projections regarding the core PCE inflation (Mishkin, 2007), we consider it as the most appropriate for our analysis. We collect the data from the FRED and we state this variable as *PCE* which in first differences gives the QoQ PCE inflation rate.

Next, since the federal funds rate was anchored at the zero lower bound over the period of our analysis, we have to rely on alternative measures in order to capture monetary policy shocks. Gambacorta, Hofmann, and Peersman (2014) find that central bank assets capture unconventional monetary policy more effectively compared to money supply measures (e.g. monetary base or M2 supply). Therefore, we use the Fed's total assets to measure monetary policy shocks. However, as a robustness check, we substitute this variable with St. Louis Adjusted Monetary Base which is a broader monetary aggregate. Again, we derive our data from the FRED and cite the variables for monetary policy and the federal funds rate as *Assets, MB* and *FFR*, respectively.

As a final step, we take the natural logarithm of the core PCE Index, Assets held by the Fed and St. Louis Adjusted Monetary Base. Concluding, Table 2 presents the descriptive statistics of the variables during the period of our analysis, Figure 2 their evolution over time and Table 3 reports the correlations of the constructed inequality measures with the previously mentioned variables.

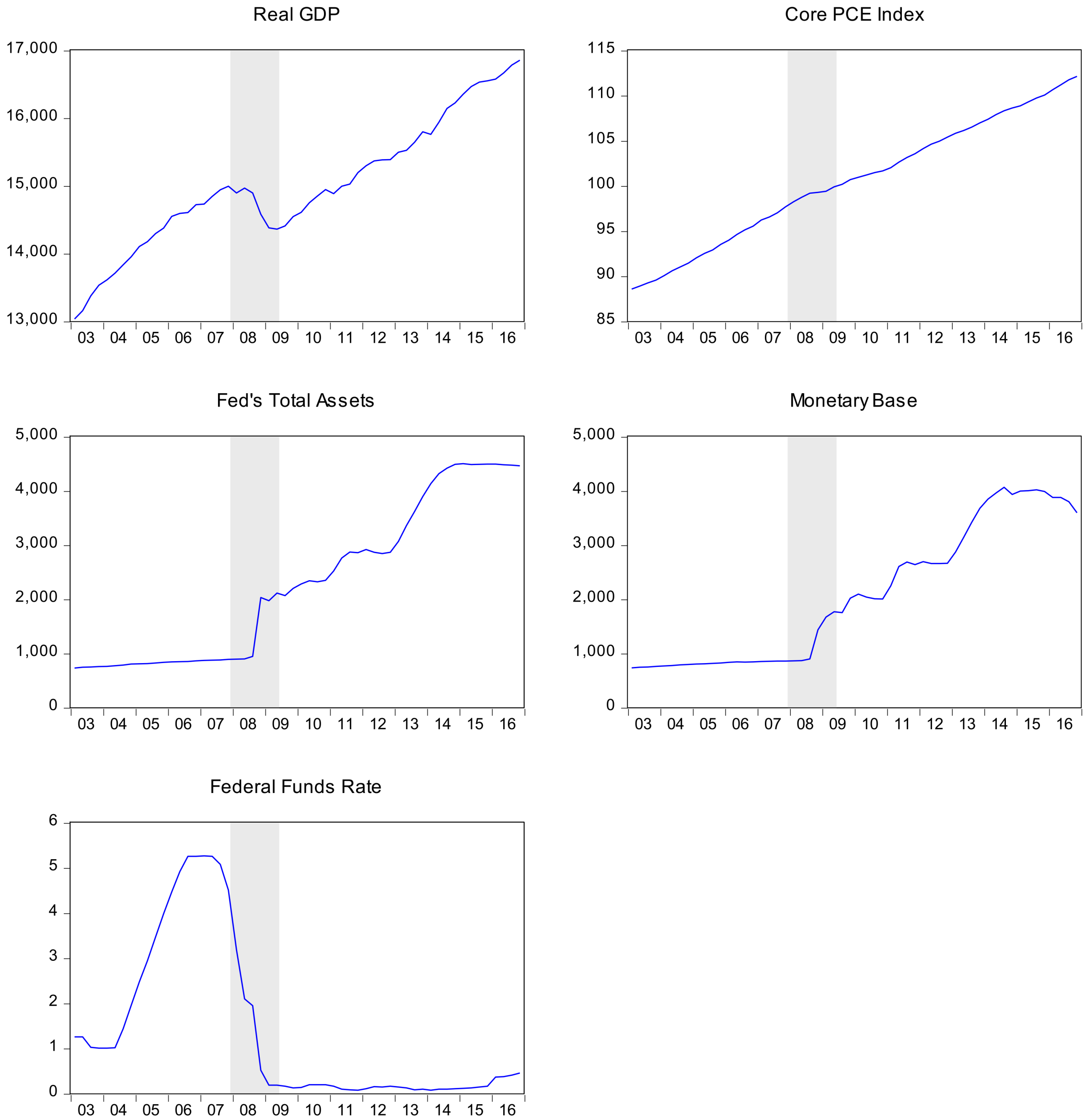
Table 2: Descriptive statistics of the variables

Variables	Unit	Mean	Min	Max	St.Dev.
RGDP	Billions of 2009 dollars	14999.11	13031.17	16851.42	953.33
PCE	Index 2009=100	100.74	87.16	111.58	7.43
Assets	Billions of dollars	2287.16	723.35	4497.30	1435.86
MB	Billions of dollars	2074.76	726.99	4059.52	1254.63
FFR	Percent	1.35	0.07	5.26	1.78

Table 3: Correlations of the variables with inequality measures

	RGDP	PCE	Assets	MB	FFR	SP500
Income Inequality						
Corr(-,Gini)	0.91	0.90	0.80	0.79	-0.30	0.76
Corr(-,90th/10th)	0.37	0.34	0.27	0.26	-0.08	0.31
Earnings Inequality						
Corr(-,Gini)	0.89	0.95	0.93	0.93	-0.60	0.75
Corr(-,90th/10th)	0.76	0.70	0.73	0.74	-0.23	0.74

Figure 2: Graphical representation of the original variables



Notes: (1) The gray shaded areas indicate the Great Recession in the U.S economy which officially started in December 2007 and lasted until June 2009. (2) All variables are presented in levels and before any transformation.

Source: FRED, Federal Reserve Bank of St. Louis

4 Methodology

In order to assess the distributional impact of the Federal Reserve's unconventional monetary policy in the U.S., and as has already been stated previously, we use a VAR model introduced by Sims (1980). This is a widely used econometric technique in monetary and macroeconomic research (Bernanke & Blinder, 1992; Bernanke & Gertler, 1995; Sack, 2000) where each variable is regressed on lagged values of itself and lagged values of a set of variables included in the model. Indeed, VAR models have established as a convenient technique to summarize the dynamic relationships of variables because once estimated, they allow to simulate the impact of disturbances (Bernanke & Gertler, 1995). From a theoretical point of view, a VAR(p) model can be expressed as follows (Lütkepohl, 2005):

$$Y_t = C + \ A_1 Y_{t-1} + ... + A_p Y_{t-p} + \ u_t$$

where k is the number of endogenous variables, A_i's are $k \times k$ coefficient matrices, C is the $k \times 1$ intercept vector, Y_t is a $k \times 1$ vector of endogenous variables and u_t is the error term representing a k-dimensional white noise process $u_t = (u_1, \ldots, u_k)$. Besides, the error term has positive defined covariance matrix $E\left(u_t u'_t\right) = \sum u$ assumed as nonsingular.

However, if there are non-stationary series, then it is possible the variables to be cointegrated which means that they present a long-run equilibrium relation. In that case, estimating a VAR model could lead to misleading conclusions (Lütkepohl, 2005; Brooks, 2014). For this reason, the first step of our empirical analysis is to determine whether the variables are stationary by analyzing their order of integration. Accordingly, to derive concrete results, we rely on three different stationarity tests (Augmented Dickey-Fuller (ADF), Phillips–Perron (PP) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS)) and we conclude based on the outcome reached by the majority.

In general, there are three different cases. First, if all series are integrated of order zero, I(0), we can use them in levels in order to estimate a VAR model. Second, when some or all of the variables are non-stationary of order one, I(1), and they are not cointegrated, we initially transform them by taking first differences and then run a VAR model. Otherwise, if there are non-stationary variables which are cointegrated, we will have to rely on a VECM. A VAR model can be expressed as a VECM of order $p-1$ as follows:

$$\Delta Y_t = C + \Pi Y_{t-1} + \Gamma_1 \Delta Y_{t-1} + ... + \Gamma_{p-1} \Delta Y_{t-p-1} + \ u_t$$

where Δy_t is the first difference of y_t, $\Pi = -(I_k - A_1 - \ ... \ - A_p)$ is a matrix which captures the long-run relationship between the variables and $\Gamma_i = -(A_{i+1} - \ ... \ - A_p)$, $i = 1, ..., p-1$ is a matrix containing the short-run parameters (Kilian & Lütkepohl, 2017).

More formally, the existence of cointegrating relationships depends on the rank of the matrix Π. If the rank (r) of matrix Π is $r > 0$, it means that the variables are cointegrated and, therefore, it would be inappropriate to estimate the VAR in first differences as it would exclude the long-run relationships between the variables. In contrast, if the rank of matrix Π is $r = 0$, which indicates that there are no cointegrated variables, a VAR in first differences is appropriately specified. Finally, when the rank of matrix $\Pi = K$, it means that all variables are stationary and a VAR in levels may be estimated (Lütkepohl, 2005).

Multiple methods have been proposed to detect cointegrated variables in a model. The two most broadly used are Engle and Granger (1987) two-step procedure and Johansen (1992) cointegration test. Gonzalo (1994) compares several methods and finds that Johansen's approach leads to better estimates allowing also the detection of multiple cointegrating equations. Furthermore, Johansen (1988) shows that the effectiveness of Engle and Granger method in a multivariate framework is limited. Therefore, we prefer and use Johansen's cointegration test. Moreover, since Johansen's test comes in at two different versions, the trace test and the maximum eigenvalue test, we follow Lütkepohl, Saikkonen, and Trenkler (2001) and choose the latter since trace test tend to have more distorted sizes when the sample size is small.

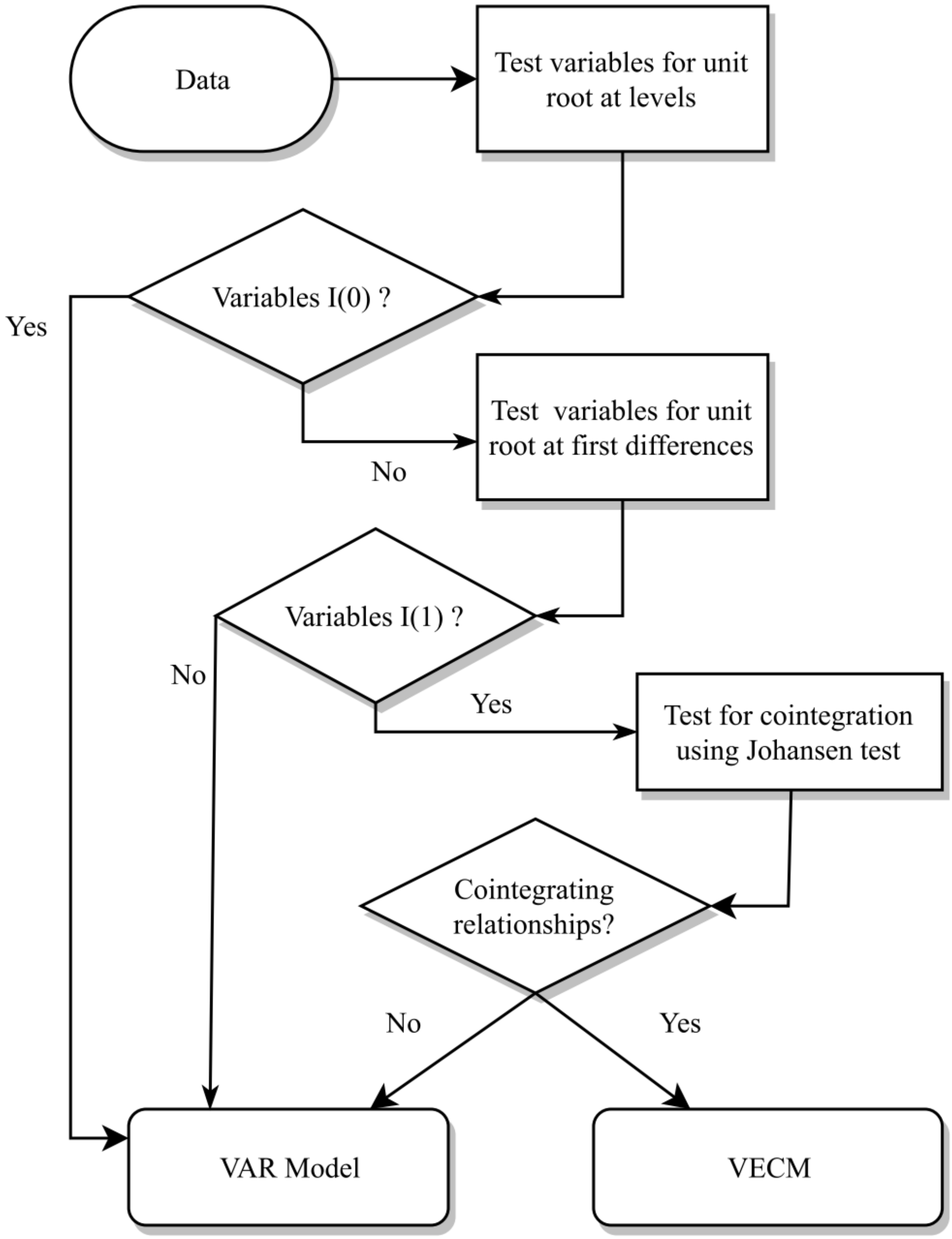
Another crucial issue in estimating a VAR model or a VECM is the specification of the lag order. Some empirical papers analyzing monetary policy shocks with quarterly data such as Sims (1986) and Christiano, Eichenbaum, and Evans (1996) include 4 lags for their estimated models. In contrast, others (Saiki and Frost (2014), Davtyan (2017)) prefer the use of various selection criteria to determine the optimal lag length. Because of the small sample size and the use of quarterly data, we follow the recommendation of the seminal paper of Venus Khim-Sen (2004) and make our initial choice about the lag length based on final prediction error (FPE) criterion. Then, we check the behavior of the residuals and the stability of the estimated model before we take our final decision. If there is autocorrelation left with the suggested lag length by FPE criterion, then we increase the lag length up to the point where there is no remaining autocorrelation.

Ultimately, it is important to make plausible assumptions and set proper restrictions concerning the contemporaneous effects among the series of our model. Hence, we follow traditional literature (e.g. Thorbecke (1997); Bernanke, Boivin, and Eliasz (2005)) and more specifically Saiki and Frost (2014), assuming that monetary policy shocks impact output and prices with a lag, while output and prices affect immediately monetary supply shocks. Consequently, the Cholesky ordering and the estimated VAR- or VEC-models are the following:

- Model Ia: RGDP, PCE inflation, Assets , Gini_Earnings
- Model Ib: RGDP, PCE inflation, Assets , Gini_Income

Also, we conduct two robustness tests in our analysis. First, we use alternative measures of inequality by replacing Gini in with the 90th/10th percentile ratio. Second, we employ the St. Louis adjusted monetary base as a variable to capture unconventional monetary policy rather than the Fed's assets. Concluding, Figure 3 summarizes and illustrates the process followed during the execution of the empirical analysis of this thesis.

Figure 3: Overview of the methodological process



Source: Authors' creation

5 Empirical analysis

In this section, we perform our empirical analysis examining the main hypothesis of this thesis being that the Fed's unconventional monetary policy has a disequalizing impact on income inequality. In doing so, we follow the methodological steps defined in the previous section. Thus, we first examine the order of integration of our variables and the optimal lag length. Next, we employ Johansen's approach to investigate if the non-stationarity is removed by cointegrating relations. Lastly, we present the impulse response functions of the estimated models and derive the results of our analysis.

5.1 Testing for stationarity

To find the order of integration of our variables we perform the following three stationary tests: the Augmented Dickey-Fuller test (ADF), the Phillips-Perron test (PP) and the Kwiatkowski-Phillips-Schmidt-Shin test (KPSS). We consider a variable as stationary or non-stationary based on the result of the majority of the tests.

First, we use the ADF test which has a null hypothesis that the variable has a unit root. The ADF test results are presented in Appendix Table A.1 and indicate that all variables in our model are non-stationarity in levels at 5%-significance level since we cannot reject the null hypothesis of a unit root. However, when we take the first differences, the ADF test suggests that all variables are stationary at 1%-significance level. Therefore, the ADF test finds that all variables are integrated of order 1.

As a second test, we employ the PP test for stationarity and display the results in Appendix Table A.2. This stationarity test controls for the serial correlation on the ADF test and has as null hypothesis that the process contains a unit root. The obtained results are in line with the findings from the ADF test. In particular, PP test suggests that all series have a unit root in levels and become stationary in first differences. Hence, once again, all the variables are integrated of order 1.

Table 4: Overview of the stationarity tests

Variables	ADF	PP	KPSS
Gini_Income	I(1)	I(1)	I(1)
Gini_Earnings	I(1)	I(1)	I(1)
RGDP	I(1)	I(1)	I(1)
PCE Inflation	I(1)	I(1)	I(1)
Assets	I(1)	I(1)	I(0)
FFR	I(1)	I(1)	I(0)

Next, we perform the non-parametric KPSS test with a null hypothesis that the series is trend-stationary and alternative hypothesis that the process has a unit root. Thus, when the null hypothesis is rejected the process has a unit root. Appendix Table A.3 presents the results of the KPSS test finding that all but two series (Assets, FFR) have a unit root at 5%-significance level whereas all processes are trend-stationary in first differences.

Overall, Table 4 provides an overview of the results obtained from the three tests. We can conclude that all variables included in our analysis are integrated of order 1 and become stationary when taken in first differences. Consequently, we have to check now if there are cointegrating relations between the variables being a necessary condition to estimate a VECM. If we find that there are no cointegrating equations, then we will estimate a VAR model with the variables in first differences.

5.2 Optimal lag structure

In this part, we determine the optimal lag length of our models. This should be a cautious decision as the number of cointegrating equations is related with the selected lag length (Emerson, 2007). For this reason, we follow the recommendation of the seminal paper of Venus Khim-Sen (2004) and make our initial choice about the lag length based on final prediction error (FPE) criterion. Then, we check the behavior of the residuals and the stability of the estimated model before we take our final decision. If there is autocorrelation left with the suggested lag length by FPE criterion, then we increase the lag length up to the point where there is no remaining autocorrelation.

Table 5 presents the lag order selection criteria for our models. Table 5a finds that all lag order selection criteria suggest one lag for Model Ia. Regarding the order of lags in Model Ib, the different selection criteria presented in Table 5b provide conflicting suggestions. In

Table 5: Lag order selection criteria for Model I

(a) Lag order selection criteria Model Ia

Lag	LogL	LR	FPE	AIC	SC	HQ
0	427.05	NA	1.01E-12	-16.27115	-16.12106	-16.21361
1	739.8068	565.3681*	1.12e-17*	-27.68488*	-26.93440*	-27.39716*
2	755.5128	25.97526	1.14E-17	-27.67357	-26.32271	-27.15568
3	764.1896	13.01518	1.56E-17	-27.39191	-25.44066	-26.64385
4	777.1466	17.44209	1.85E-17	-27.27487	-24.72324	-26.29663

(b) Lag order selection criteria for Model Ib

Lag	LogL	LR	FPE	AIC	SC	HQ
0	427.902	NA	9.76E-13	-16.30392	-16.15383	-16.24638
1	744.4164	572.1606	9.35E-18	-27.86217	-27.11169*	-27.57445*
2	764.3183	32.91468*	8.14e-18*	-28.01224*	-26.66138	-27.49435
3	776.3751	18.08515	9.75E-18	-27.86058	-25.90934	-27.11252
4	787.9356	15.56226	1.22E-17	-27.68983	-25.1382	-26.7116

Notes: * indicates lag order selected by the criterion; LR: sequential modified LR test statistic (each test at 5% level); FPE: Final prediction error; AIC: Akaike information criterion; SC: Schwarz information criterion; HQ: Hannan-Quinn information criterion particular LR, FPE and AIC criteria recommend the use of two lags while SC and HQ propose only one. However, when we check the behavior of the residuals we find that there is autocorrelation left when we use a lag of order one for Model Ia while the residuals of the other model are free from autocorrelation. Therefore, after checking the behavior of the residuals, we conclude that it is optimal to include four lags for Model Ia and two lags for Model Ib.

5.3 Johansen's cointegration approach

The next step in our analysis is to examine whether there are cointegrating relationships between the variables. For this reason we employ Johansen's approach and use the cointegration rank maximum eigenvalue test. Table 6 presents the results of the Johansen method for our models.

For Model Ia, the maximum eigenvalue test indicates that there are no cointegrating equations in the system. Thus, we estimate Model Ia with a VAR(4) model and the variables in first differences. Contrarily, we find three cointegrating equations in Model Ib which implies that Model Ib should be estimated using a VECM(1) model with the variables in levels. Before proceeding with the estimation of the specified models and the impulse response functions, we assess if our models are correctly specified. Thus, we check whether the stability conditions are satisfied and if our models are free from autocorrelation for the selected number of lags. The results, presented in Appendix Figure A.3 and Table A.4, highlight that both conditions are satisfied and the models are appropriately specified.

Table 6: Cointegration Rank Test Trace statistics Model I

(a) Cointegration rank maximum eigenvalue test Model Ia

No. of CE(s)	Eigenvalue	Max-Eigen Statistic	Critical Value (0.05)	Prob.**
None	0.314484	19.25677	27.58434	0.3949
At most 1	0.239600	13.96943	21.13162	0.3675
At most 2	0.153842	8.519479	14.26460	0.3283
At most 3	0.062494	3.291161	3.841466	0.0696

(b) Cointegration rank maximum eigenvalue test Model Ib

No. of CE(s)	Eigenvalue	Max-Eigen Statistic	Critical Value (0.05)	Prob.**
None *	0.455065	32.17571	27.58434	0.0119
At most 1 *	0.332803	21.44752	21.13162	0.0451
At most 2 *	0.268495	16.57048	14.26460	0.0212
At most 3	0.053347	2.905617	3.841466	0.0883

5.4 Estimated results

Having specified the lag structure and the number of cointegrating equations, we are now able to estimate Model Ia with a VAR model in first differences and Model Ib with a VECM. These estimates can be found in Appendices A.5 and A.6. Given the large amount of IRFs, in this section we have opted to discuss only selected impulse response functions (IRF) derived from the estimated models. Nevertheless, all IRFs can be found in Appendices A.7 and A.8. It should be noted that an IRF represents the effect of a one-time shock in a series and allows to capture the current and future impacts on the rest of the endogenous variables. For IRFs, we impose a shock of one standard deviation in our variables and track the effect over 10 quarters or 2.5 years.

Figure 4 and Figure 5 depict the effect of two innovations on Gini: (i) Real GDP and (ii) Assets. Model Ia and Model Ib include Gini variables for total income and labor income, respectively. From the former, we observe that 1% increase in GDP reduces total income inequality during the first year but then the effect reverses and, finally, fades out after about 2 years. Moreover, we see the effect of 1% increase in the amount of assets held by the Fed has, if something, an unclear impact on the Gini variable based on total income.

Figure 4: Model Ia: Response of Gini to Real GDP and Assets held by the Fed

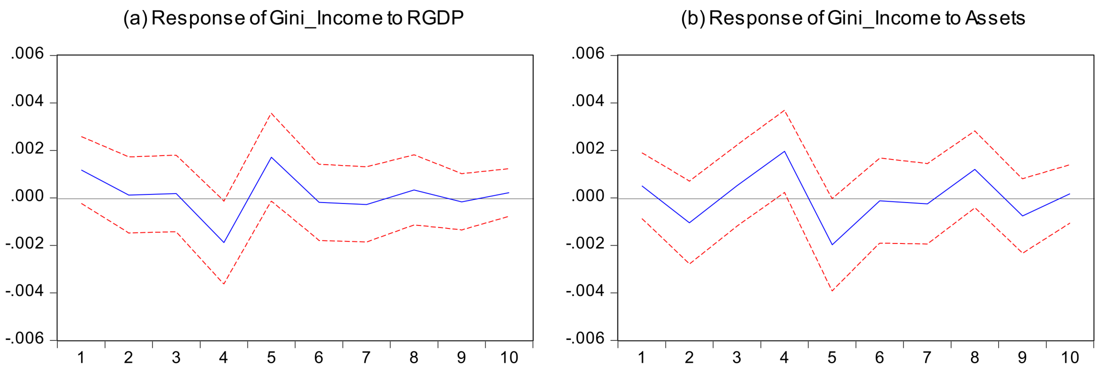
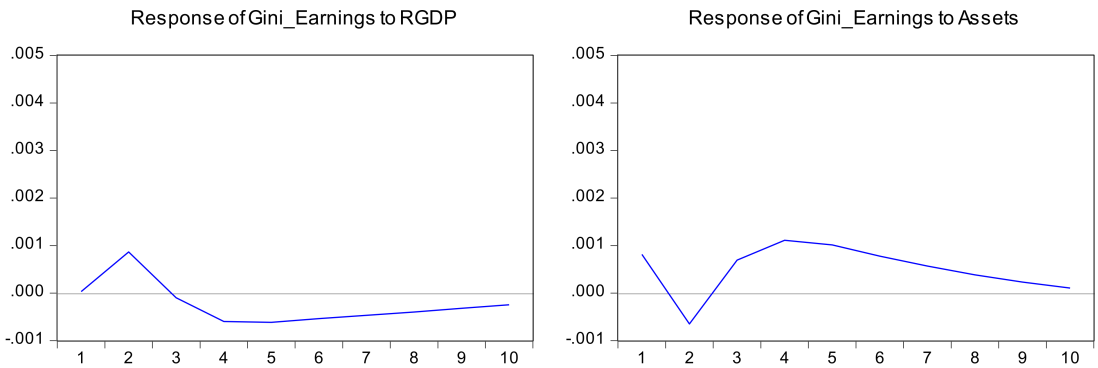


Figure 5: Model Ib: Response of Gini to Real GDP and Assets held by the Fed



Notes: (1) Red lines indicate confidence intervals. (2) The econometric program Eviews does not provide the confidence intervals when a VECM is estimated.

Concerning the IRFs of the latter, we observe that economic growth leads to a more equal labor income distribution from the second quarter and onwards. Furthermore, using labor income, the unconventional monetary policy appears to have a positive effect on lower income groups initially but after two quarters the effect turns out to lead to less equal labor income distribution when we impose an innovation of 1% Fed's assets. Therefore, we find evidence that the earnings heterogeneity channel leads to a temporary increase on inequality. One possible explanation for the positive and negative results on assets' held by the Fed and the economic growth up to the second quarter respectively, could be that the impact of the QE appears on labor earning with a two quarters delay.

In addition, juxtaposing the results of Model Ia and Model Ib, we can infer that this is evidence for the existence of the income composition channel, but the quality and reliability of the wealth data on CEX do not allow us to decompose the effect of the QE on total before-tax income and labor income.

Overall, we find that the effect of unconventional monetary policy has a negative impact on labor income supporting the idea that low-income and high-income groups may be affected differently from monetary policy shocks. On possible explanation for the increase in inequality could be associated with the fact that the QE affects primarily asset-prices rather that real economy. However, when taking into account total before-tax income, the QE appears to have an unclear impact but we believe that this result is affected by the quality of the CEX total before-tax income data.

5.5 Sensitivity analysis

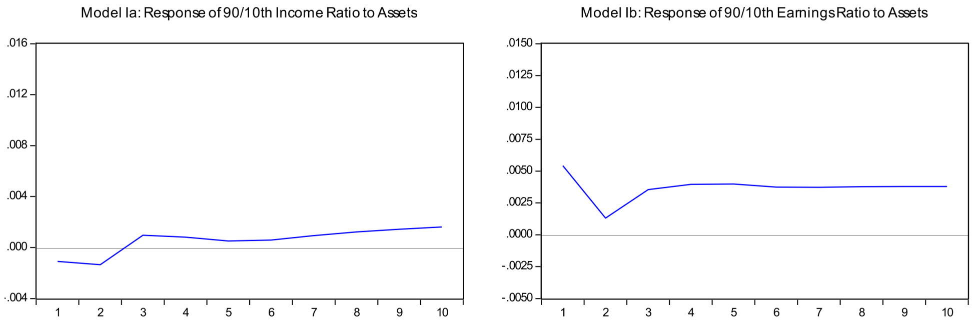
As a final step of our empirical analysis, we conduct two different robustness checks. First, we replace the Gini coefficient variables with the 90/10th percentile ratios (See Section 3.1.1). Second, we use the St. Louis Adjusted Monetary Base instead of Asset's held by the Fed as a variable for monetary easing. In all the cases, we repeat the methodological steps followed in Section 5, but we do present only the relevant IRFs.

5.5.1 Alternative inequality variable

In our basic empirical analysis, we use Gini as the main variable to gauge total income and earnings distribution. As a robustness check, we now substitute Gini with the 90/10th percentile ratio. All the variables are I(1) again and all four models have at least one cointegrating relation. Thus, we estimate them using VECM.

Figure 6 presents IRFs when we shock the amount of the Fed's assets by 1%. Whereas using an alternative variable for inequality yields identical results regarding the impact of monetary easing on earnings inequality, the results differ substantially for total before-tax income. In that case, Model Ia reduces inequality over the short-run but leads to more unequal distribution over the medium and long term which is close but not similar to the received response with Gini coefficient. Contrarily, the shape of the response obtained in Model Ib is similar to the one obtained using the Gini coefficient. However, the impact does not fade out over time. Consequently, we can conclude that the obtained findings are robust for earnings inequality but not for total income inequality with one possible explanation to be the superior quality of labor income data compared to the total income in the CEX.

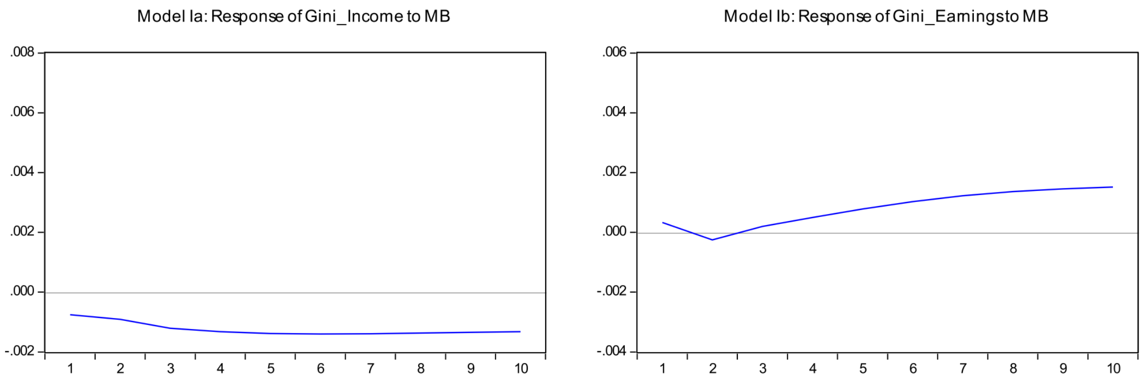
Figure 6: Response of 90/10th percentile ratio to Assets held by the Fed



5.5.2 Different variable for monetary policy

For the next sensitivity test, we change the measure of unconventional monetary policy from the Fed's assets to the St. Louis Adjusted Monetary Base. Then we run again Model Ia and Model Ib presenting the relevant IFRs in Figure 7. Again, we see that the outcome for a more unequal labor income distribution survives while inequality in the distribution of total before-tax income fails again the robustness check.

Figure 7: Response of Gini to Monetary Base



6 Conclusions

The combination of the unconventional monetary policy as a response to combat the Great Recession and evidence of growing inequality in developed countries has brought the distributional consequences of monetary policy into the spotlight. Therefore, the goal of this empirical paper was to analyze the distributional impact of the Fed's unconventional monetary policy on income inequality. In order to do so, we used household survey data from the CEX of the U.S. Bureau of Labor Statistics to construct measures of inequality for total before-tax income and labor earnings on a quarterly basis. Accordingly, this enabled our research to provide insights on the unintended distributional consequences of the unconventional monetary policy followed by the Fed in the U.S. More specifically, we aim to answer whether an increase in the Fed's balance sheet has a disequalizing impact on income inequality using VAR model and VECM.

Overall, our findings indicate that unconventional monetary policy worsens labor earning distribution with the result being significant and consistent with different measures of monetary easing and income inequality variables. Indeed, we found evidence that QE leads to higher inequality through the earnings heterogeneity channel. In contrast, the impact on total income distribution found to be ambiguous and inconsistent between different specifications. However, given the difference with the results for labor income, we can infer that this is evidence for the existence of the income composition channel, but the quality and reliability of the wealth data on CEX do not allow us to decompose the effect of the QE on the total before-tax income and labor income.

Concluding, we note that although the use of CEX data solves the frequency problem of obtaining quarterly inequality variables, our analysis has some considerable limitations. First, and most importantly, the CEX excludes the top 1% of the income distribution which in the period 2009-2015 recorded a real income growth of 37.4% against an average of 13% and a rise of 7.6% at the bottom 99% of the income distribution (Saez, 2015). Therefore, the constructed inequality measures could underestimate the distributional impact of monetary policy shocks. Second, since we use survey data, the constructed measures of income inequality are of lower quality compared to those from administrative data due to the measurement errors (Groves, 2004). Ideally, we would like to employ data from the triennial SCF to construct our inequality variables as the survey provides an unparalleled amount of high quality data with regards to household's balance sheet but for reasons described in Section 3 we could not.

References

Adam, K., & Tzamourani, P. (2016). Distributional Consequences of Asset Price Inflation in the Euro Area. *European Economic Review*, *89*, 172 - 192. Retrieved from https://doi.org/10.1016/j.euroecorev.2016.07.005

Albanesi, S. (2007). Inflation and Inequality. *Journal of Monetary Economics*, *54*(4), 1088 - 1114. Retrieved from https://doi.org/10.1016/j.jmoneco.2006.02.009

Auda, H. (2010). *New tests of symmetry in regression models: application to the relation between income inequality and inflation* [manuscript].

Bank of England, B. o. E. (2012). The Distributional Effects of Asset Purchases. *Bank of England Quarterly Bulletin*, *52*(3), 254-266. Retrieved from https://EconPapers.repec.org/RePEc:boe:qbullt:0085

Bernanke, B. S. (2015). Monetary Policy and Inequality. *Ben Bernanke's Blog at Brookings*. Retrieved from https://brook.gs/2Jf7Ktv

Bernanke, B. S., & Blinder, A. S. (1992). The Federal Funds Rate and the Channels of Monetary Transmission. *The American Economic Review*, *82*(4), 901–921. Retrieved from http://www.jstor.org/stable/2117350

Bernanke, B. S., Boivin, J., & Eliasz, P. (2005). Measuring the Effects of Monetary Policy: A Factor-Augmented Vector Autoregressive (FAVAR) Approach. *The Quarterly Journal of Economics*, *120*(1), 387-422. Retrieved from http://dx.doi.org/10.1162/0033553053327452

Bernanke, B. S., & Gertler, M. (1995). Inside the Black Box: The Credit Channel of Monetary Policy Transmission. *The Journal of Economic Perspectives*, *9*(4), 27–48. Retrieved from http://www.jstor.org/stable/2138389

Brooks, C. (2014). *Introductory Econometrics for Finance*. Cambridge university press.

Brunnermeier, M. K., & Sannikov, Y. (2012). Redistributive Monetary Policy. *Proceedings - Economic Policy Symposium - Jackson Hole*, 331-384. Retrieved from https://ideas.repec.org/a/fip/fedkpr/y2012p331-384.html

Bulir, A. (2001). Income Inequality: Does Inflation Matter? *IMF Staff Papers*, *48*(1), 139–159. Retrieved from http://www.jstor.org/stable/4621662

Bureau of Labor Statistics. (2017, August 29). *Getting Started with Consumer Expenditure Survey (CE) Public-Use Microdata (PUMD)* [Documentation]. Retrieved from https://bit.ly/2xuMBdu

Casiraghi, M., Gaiotti, E., Rodano, L., & Secchi, A. (2018). A "reverse Robin Hood"? The Distributional Implications of Non-Standard Monetary Policy for Italian Households. *Journal of International Money and Finance*, *85*, 215 - 235. Retrieved from https://doi.org/10.1016/j.jimonfin.2017.11.006

Christiano, L., Eichenbaum, M., & Evans, C. L. (1996). Identification and the Effects of Monetary Policy Shocks. *Financial Factors in Economic Stabilization and Growth*, 36.

Coibion, O., Gorodnichenko, Y., Kueng, L., & Silvia, J. (2017). Innocent Bystanders? Monetary Policy and Inequality. *Journal of Monetary Economics*, *88*, 70 - 89. Retrieved from https://doi.org/10.1016/j.jmoneco.2017.05.005

Davtyan, K. (2017). The Distributive Effect of Monetary Policy: The Top One Percent Makes the Difference. *Economic Modelling*, *65*, 106 - 118. Retrieved from https://doi.org/10.1016/j.econmod.2017.05.011

Deutsche Bundesbank. (2016, September). Distributional Effects of Monetary Policy. *Deutsche Bundesbank Monthly Reports*. Retrieved from https://bit.ly/2KJYEoH

Dobbs, R., Lund, S., Koller, T., & Shwayder, A. (2013). QE and Ultra-Low Interest Rates: Distributional Effects and Risks. *McKinsey Global Institute Discussion Paper*. Retrieved from https://mck.co/2JubEhQ

Doepke, M., & Schneider, M. (2006). Inflation and the Redistribution of Nominal Wealth. *Journal of Political Economy*, *114*(6), 1069-1097. Retrieved from https://doi.org/10.1086/508379

Doepke, M., Schneider, M., & Selezneva, V. (2015). Distributional Effects of Monetary Policy [2015 Meeting Papers 1099]. *Society for Economic Dynamics*. Retrieved from https://ideas.repec.org/p/red/sed015/1099.html

Domanski, D., Scatigna, M., & Zabai, A. (2016). Wealth Inequality and Monetary Policy. *BIS Quarterly Review*, 45. Retrieved from https://ssrn.com/abstract=2744862

Draghi, M. (2015, May 14). *The ECB's recent monetary policy measures: Effectiveness and challenges.* Retrieved from https://bit.ly/1GbwoGm (Camdessus lecture at International Monetary Fund,Washington, D.C.)

Easterly, W., & Fischer, S. (2001). Inflation and the Poor. *Journal of Money, Credit and Banking*, *33*(2), 160–178. Retrieved from http://www.jstor.org/stable/2673879

Emerson, J. (2007). Cointegration Analysis and the Choice of Lag Length. *Applied Economics Letters*, *14*(12), 881-885. Retrieved from https://doi.org/10.1080/13504850600689956

Engle, R. F., & Granger, C. W. J. (1987). Co-Integration and Error Correction: Representation, Estimation, and Testing. *Econometrica*, *55*(2), 251–276. Retrieved from http://www.jstor.org/stable/1913236

Erosa, A., & Ventura, G. (2002). On Inflation as a Regressive Consumption Tax. *Journal of Monetary Economics*, *49*(4), 761 - 795. Retrieved from https://doi.org/10.1016/S0304-3932(02)00115-0

Federal Reserve. (2012). Federal Reserve Issues FOMC Statement of Longer-Run Goals and Policy Strategy. *press release*, *25*. Retrieved from https://bit.ly/2JahI2B

Furceri, D., Loungani, P., & Zdzienicka, A. (2018). The Effects of Monetary Policy Shocks on Inequality. *Journal of International Money and Finance*, *85*, 168 - 186. Retrieved from https://doi.org/10.1016/j.jimonfin.2017.11.004

Galbraith, J. K., Giovannoni, O., & Russo, A. J. (2007). *The Fed's Real Reaction Function: Monetary Policy, Inflation, Unemployment, Inequality and Presidential Politics* (No. 511). Levy Economics Institute of Bard College. Retrieved from http://hdl.handle.net/10419/31514

Galli, R., & van der Hoeven, R. (2001). Is Inflation Bad for Income Inequality: The

Importance of the Initial Rate of Inflation. *ILO Employment Paper*(29).

Gambacorta, L., Hofmann, B., & Peersman, G. (2014). The Effectiveness of Unconventional Monetary Policy at the Zero Lower Bound: A Cross-Country Analysis. *Journal of Money, Credit and Banking*, *46*(4), 615-642. Retrieved from https://doi.org/10.1111/jmcb.12119

Gonzalo, J. (1994). Five Alternative Methods of Estimating Long-Run Equilibrium Relationships. *Journal of Econometrics*, *60*(1), 203 - 233. Retrieved from https://doi.org/10.1016/0304-4076(94)90044-2

Gornemann, N., Kuester, K., & Nakajima, M. (2016, May). *Doves for the Rich, Hawks for the Poor? Distributional Consequences of Monetary Policy* (International Finance Discussion Papers No. 1167). Board of Governors of the Federal Reserve System (U.S.). Retrieved from https://doi.org/10.17016/IFDP.2016.1166

Groves, R. M. (2004). *Survey errors and survey costs* (Vol. 536). John Wiley & Sons.

Johansen, S. (1988). Statistical Analysis of Cointegration Vectors. *Journal of Economic Dynamics and Control*, *12*(2), 231 - 254. Retrieved from https://doi.org/10.1016/0165-1889(88)90041-3

Johansen, S. (1992). Cointegration in Partial Systems and the Efficiency of Single-Equation Analysis. *Journal of Econometrics*, *52*(3), 389 - 402. Retrieved from https://doi.org/10.1016/0304-4076(92)90019-N

Kilian, L., & Lütkepohl, H. (2017). *Structural vector autoregressive analysis*. Cambridge University Press. Retrieved from https://doi.org/10.1017/9781108164818

Kuznets, S. (1955). Economic Growth and Income Inequality. *The American Economic Review*, *45*(1), 1–28. Retrieved from http://www.jstor.org/stable/1811581

Lansing, K. J., & Markiewicz, A. (2016). Top Incomes, Rising Inequality and Welfare. *The Economic Journal*, *128*(608), 262-297. Retrieved from https://doi.org/10.1111/ecoj.12411

Li, H., & Zou, H.-f. (2002). Inflation, Growth, and Income Distribution: A Cross-Country Study. *Annals of Economics and Finance*, *3*(1), 85–101. Retrieved from https://bit.ly/2GNAsPU

Lütkepohl, H. (2005). *New introduction to multiple time series analysis*. Springer Science & Business Media. Retrieved from https://doi.org/10.1007/978-3-540-27752-1

Lütkepohl, H., Saikkonen, P., & Trenkler, C. (2001). Maximum Eigenvalue Versus Trace Tests for the Cointegrating Rank of a VAR Process. *The Econometrics Journal*, *4*(2), 287-310. Retrieved from https://doi.org/10.1111/1368-423X.00068

McCully, C. P., Moyer, B. C., & Stewart, K. J. (2007). Comparing the Consumer Price Index and the Personal Consumption Expenditures Price Index. *Survey of Current Business*, *87*(11), 26–33. Retrieved from https://bit.ly/2xlURw9

Mishkin, F. S. (2007, October 20). *Headline versus core inflation in the conduct of monetary policy: a speech at the Business Cycles, International Transmission and Macroeconomic Policies Conference* (Speech No. 332). Retrieved from https://bit.ly/2sgU6zA

Montecino, J. A., & Epstein, G. (2015). Did Quantitative Easing Increase Income Inequality? *Institute for New Economic Thinking (INET) Working Paper Series*(28). Retrieved from https://bit.ly/2xd2ipe

Mumtaz, H., & Theophilopoulou, A. (2017). The Impact of Monetary Policy on Inequality in the UK. An Empirical Analysis. *European Economic Review*, *98*, 410 - 423. Retrieved from https://doi.org/10.1016/j.euroecorev.2017.07.008

O'Farrell, R., Rawdanowicz, L., & Inaba, K.-I. (2016). Monetary Policy and Inequality. *OECD Economics Department Working Papers*(1281). Retrieved from http://dx.doi.org/10.1787/5jm2hz2x9hxr-en

Romer, C. D., & Romer, D. (1999). Monetary Policy and the Well-Being of the Poor. *Economic Review*(Q I), 21-49. Retrieved from https://bit.ly/2IMUdJt

Sack, B. (2000). Does the Fed Act Gradually? A VAR Analysis. *Journal of Monetary Economics*, *46*(1), 229 - 256. Retrieved from https://doi.org/10.1016/S0304-3932(00)00019-2

Saez, E. (2015, January). Striking it Richer: The Evolution of Top Incomes in the United States (updated with 2013 preliminary estimates). *Berkeley: University of California, Department of Economics*. Retrieved from https://bit.ly/2H6ob9r

Saiki, A., & Frost, J. (2014). Does Unconventional Monetary Policy Affect Inequality? Evidence from Japan. *Applied Economics*, *46*(36), 4445-4454. Retrieved from https://doi.org/10.1080/00036846.2014.962229

Sims, C. A. (1980). Macroeconomics and Reality. *Econometrica*, *48*(1), 1–48. Retrieved from http://www.jstor.org/stable/1912017

Sims, C. A. (1986). Are Forecasting Models Usable for Policy Analysis. *Quarterly Review, Federal Reserve Bank of Minneapolis*, 2–16. Retrieved from https://bit.ly/2J74PqD

Thalassinos, E., Ugurlu, E., & Muratoglu, Y. (2012). Income Inequality and Inflation in the EU. *European Research Studies*, *15*(1), 127-140. Retrieved from https://bit.ly/2JaYAhD

Thorbecke, W. (1997). On Stock Market Returns and Monetary Policy. *The Journal of Finance*, *52*(2), 635-654. Retrieved from http://dx.doi.org/10.1111/j.1540-6261.1997.tb04816.x

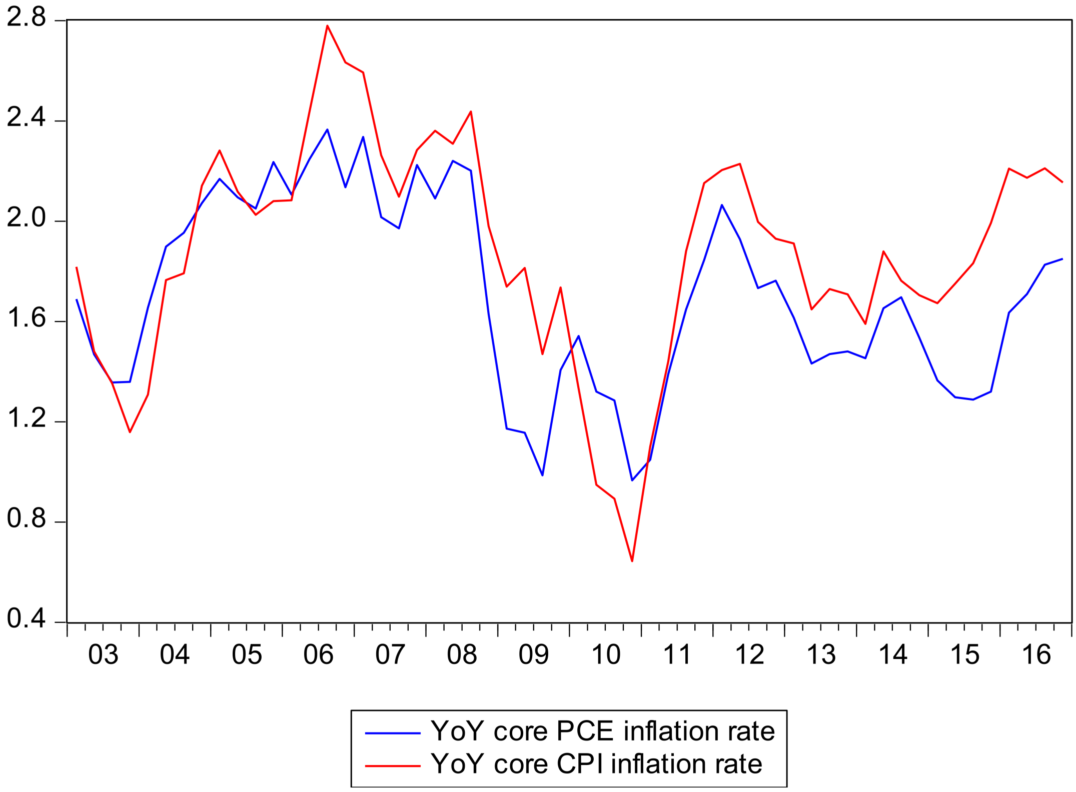
Venus Khim-Sen, L. (2004). Which Lag Length Selection Criteria Should We Employ. *Economics Bulletin*, *3*, 1-9. Retrieved from https://bit.ly/2LjEPbO

Yellen, J. (2014). *Perspectives on inequality and opportunity from the survey of consumer finances: a speech at the conference on economic opportunity and inequality, federal reserve bank of boston, boston, massachusetts, october 17, 2014* (Speech No. 821). Board of Governors of the Federal Reserve System (U.S.). Retrieved from https://EconPapers.repec.org/RePEc:fip:fedgsq:821

A Appendices

A.1 Comparison core PCE vs core CPI

Figure A.1: Comparison between core PCE and core CPI inflation rate



Source: FRED, Federal Reserve Bank of St. Louis

A.2 Stationarity tests

Table A.1: Stationarity test: Augmented Dickey-Fuller

(a) Stationarity test: ADF for the levels of the variables

Variables	Exogenous Terms	Lag Length	Test Statistic
Gini_Income	constant	0	-1.87
Gini_Earnings	constant	0	-1.80
RGDP	constant, trend	1	-2.36
PCE	constant, trend	1	-1.38
Assets	constant, trend	1	-2.02
FFR	constant	3	-2.87*

(b) Stationarity test: ADF for the variables in first differences

Variables	Exogenous Terms	Lag Length	Test Statistic
ΔGini_Income	none	0	-8.80***
ΔGini_Earnings	none	0	-9.10***
ΔRGDP	constant	0	-4.52***
ΔPCE	constant	0	-5.08***
ΔAssets	constant	0	-7.26***
ΔFFR	none	0	-3.40***

Notes: (1) * $p < 0{:}10$, ** $p < 0{:}05$, *** $p < 0{:}01$. (2) ADF critical values for neither a constant nor trend are: -1.61 (10%), -1.95 (5%), and -2.61 (1%). ADF critical values with only a constant are: -2.59 (10%), -2.91 (5%), and -3.56 (1%). ADF critical values with both a constant and a linear trend are: -3.18 (10%), -3.49 (5%), and -4.13 (1%). (3) The choice of lagged differences is based on Schwartz information criterion. (4) We consider a variable as stationary if we can reject the null hypothesis of a unit root at 5% level.

Table A.2: Stationarity test: Phillips-Perron

(a) Stationarity test: Phillips-Perron for the levels of the variables

Variables	Exogenous Terms	Bandwidth	Test Statistic
Gini_Income	constant	7	-1.61
Gini_Earnings	constant	3	-1.04
RGDP	constant, trend	4	-2.07
PCE Inflation	constant	4	-1.56
Assets	constant, trend	1	-2.08
FFR	none	5	-1.25

(b) Stationarity test: Phillips-Perron for the variables in first differences

Variables	Exogenous Terms	Bandwidth	Test Statistic
ΔGini_Income	none	3	-8.95***
ΔGini_Earnings	none	1	-9.13***
ΔRGDP	constant	2	-4.52***
ΔPCE Inflation	constant	4	-5.16***
ΔAssets	constant	2	-7.27***
ΔFFR	none	5	-3.56***

Notes: (1) * $p < 0{:}10$, ** $p < 0{:}05$, *** $p < 0{:}01$. (2) PP critical values for neither a constant nor a trend are: -1.61 (10%), -1.95 (5%), and -2.63 (1%). PP critical values with only a constant are: -2.61 (10%), -2.95 (5%), and -3.63 (1%). PP critical values with both a constant and a linear trend are: -3.20 (10%), -3.54 (5%), and -4.25 (1%). (3) The choice of bandwidth is based on Newey-West Bartlett kernel. (4) We consider a variable as stationary if we can reject the null hypothesis of a unit root at 5% level.

Table A.3: Stationarity test: Kwiatkowski–Phillips–Schmidt–Shin

(a) Stationarity test: KPSS for the levels of the variables

Variables	Deterministic Terms	Bandwidth	Test Statistic
Gini_Income	constant	5	0.93***
Gini_Earnings	constant	6	0.88***
RGDP	constant, trend	5	0.16**
PCE Inflation	constant, trend	6	0.19**
Assets	constant, trend	5	0.11
FFR	constant	6	0.42*

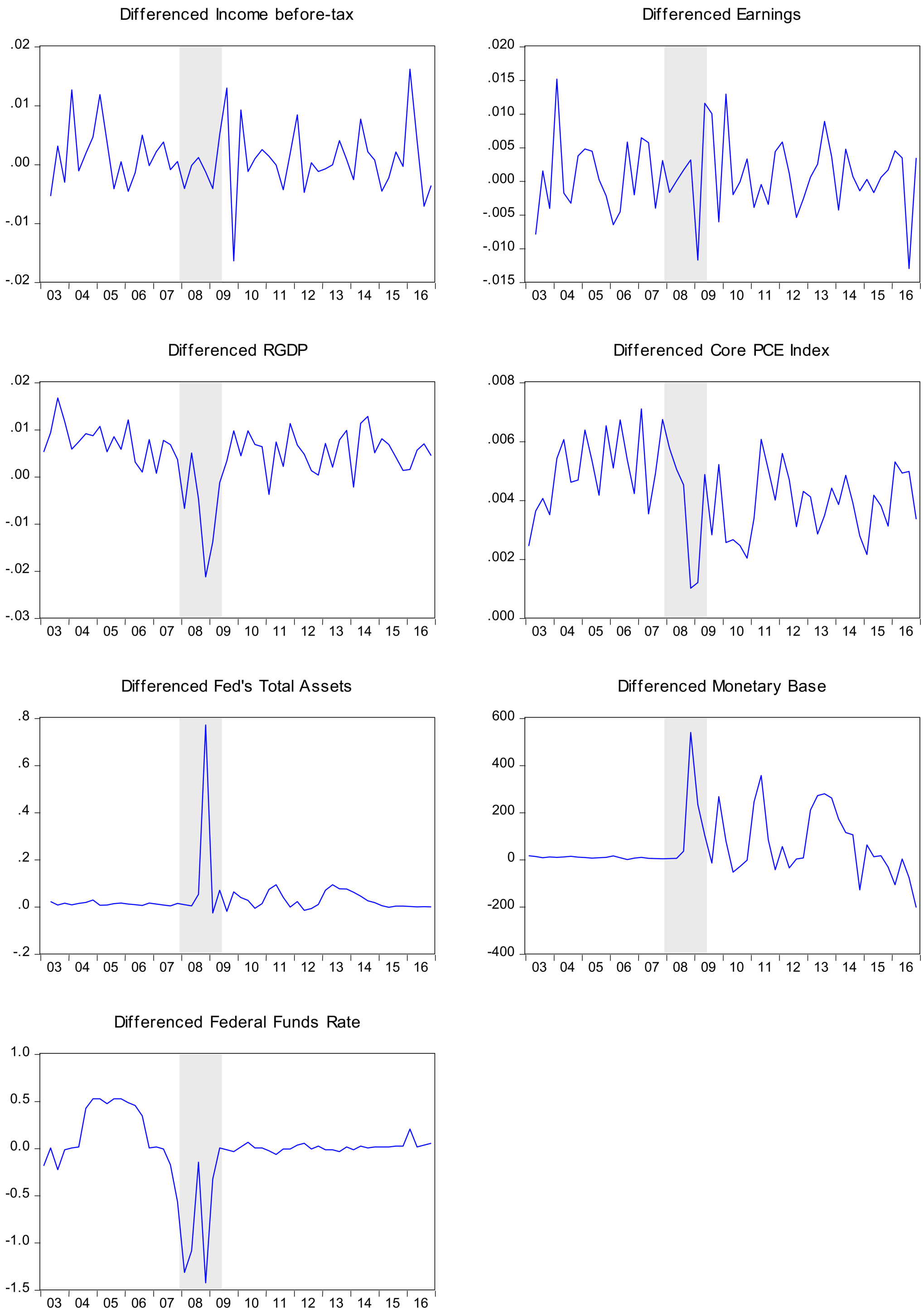
(b) Stationarity test: KPSS for the variables in first differences

Variables	Deterministic Terms	Bandwidth	Test Statistic
ΔGini_Income	constant	12	0.13
ΔGini_Earnings	constant	6	0.07
ΔRGDP	constant	4	0.15
ΔPCE Inflation	constant	4	0.29
ΔAssets	constant	2	0.09
ΔFFR	constant	5	0.10

Notes: (1) * $p < 0:10$, ** $p < 0:05$, *** $p < 0:01$. (2) KPSS critical values with only a constant are: 0.35 (10%), 0.46 (5%), and 0.74 (1%). KPSS critical values with both a constant and a linear trend are: 0.12 (10%), 0.15 (5%), and 0.22 (1%). (3) The choice of bandwidth is based on Newey-West Bartlett kernel. (4) We consider a variable as stationary if we fail to reject the null hypothesis of no unit root at 5% level.

A.3 Graphical representation of the variables in first differences

Figure A.2: Graphical representation of the variables in first differences



Note: The gray shaded areas indicate the Great Recession in the U.S economy which officially started in December 2007 and lasted until June 2009.

Source: FRED, Federal Reserve Bank of St. Louis and Bloomberg

A.4 Stability diagnostics of the estimated models

A.4.1 Autocorrelation LM test

Table A.4: Autocorrelation LM test

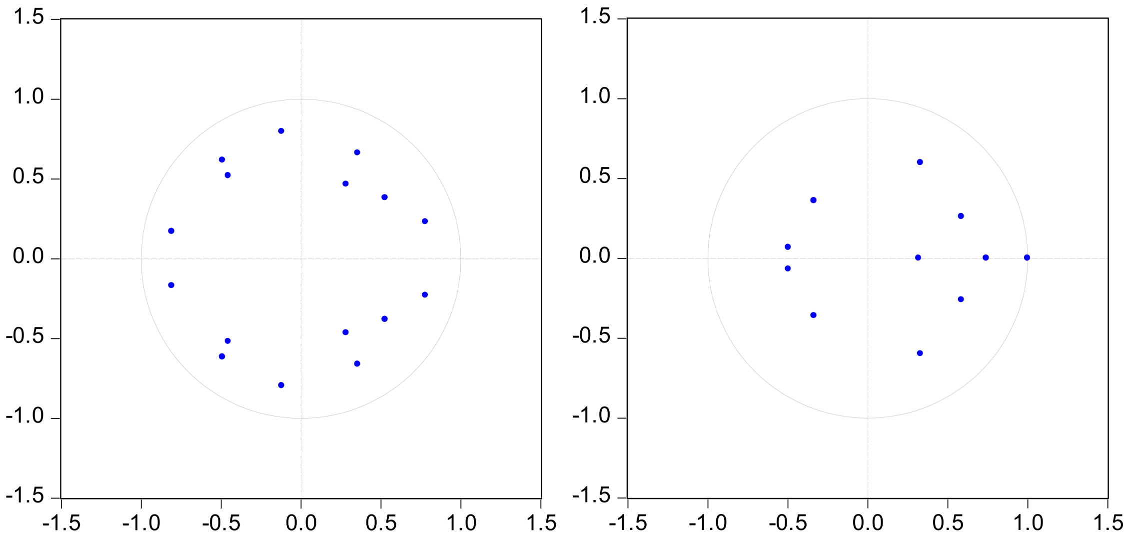
	Model Ia		Model Ib	
Lags	LM-Stat	Prob	LM-Stat	Prob
1	12.76724	0.6897	19.10160	0.2634
2	9.146593	0.9073	18.31976	0.3055
3	15.16624	0.5125	14.78828	0.5402
4	21.19332	0.1712	14.15673	0.5870
5	21.7836	0.1503	19.27498	0.2547
6	22.52736	0.1270	14.97921	0.5262
7	13.38295	0.6446	11.81224	0.7568
8	13.93325	0.6037	11.80565	0.7572
9	13.41609	0.6421	8.64997	0.9271
10	31.54924	0.0114	28.32172	0.0289
11	16.87447	0.3938	15.09544	0.5177
12	17.54340	0.3513	11.27931	0.7919

Note: Probabilities from chi-square with 16 degrees of freedom for Model Ia and Ib.

A.4.2 Inverse roots of AR characteristic polynomial

The estimated VAR is stable when all roots have modulus less than one and lie inside the unit circle. If the VAR is unstable then the estimated results are invalid. Moreover, when we estimate a VECM with cointegrating equations there should be N-r unit moduli where N is the number of endogenous variables and r is the number of cointegrating equations. In Model Ia, we find that all roots of the VAR lie inside the circle and, therefore, the VAR model is stable. Next, we find that Model Ib has two unit moduli which means that the stability conditions are also satisfied.

Figure A.3: Inverse roots of AR characteristic polynomial



(a) Model Ia: VAR(4)

(b) Model Ib: VECM(1)

A.5 Estimation of the Model Ia: VAR(4)

Table A.5: VAR(4) - Model Ia

	D(LRGDP)	D(PCE Inflation)	D(Assets)	D(Gini_Income)
D(LRGDP(-1))	0.163902	0.001374	-3.900035	-0.047495
	(0.18378)	(0.04134)	(3.70171)	(0.16930)
	[0.89182]	[0.03323]	[-1.05358]	[-0.28053]
D(LRGDP(-2))	0.231675	-0.059594	1.141558	0.104155
	(0.18415)	(0.04142)	(3.70898)	(0.16963)
	[1.25811]	[-1.43860]	[0.30778]	[0.61399]
D(LRGDP(-3))	0.306424	0.067070	-8.948990	-0.137499
	(0.18319)	(0.04121)	(3.68974)	(0.16875)
	[1.67271]	[1.62753]	[-2.42537]	[-0.81479]
D(LRGDP(-4))	0.010770	0.066704	-0.999713	0.097534
	(0.16950)	(0.03813)	(3.41401)	(0.15614)
	[0.06354]	[1.74937]	[-0.29283]	[0.62464]
D(PCE Inflation(-1))	0.728621	0.367897	-11.47835	-0.534799
	(0.74569)	(0.16775)	(15.0195)	(0.68693)
	[0.97710]	[2.19313]	[-0.76423]	[-0.77853]
D(PCE Inflation(-2))	0.111482	0.049613	-1.876781	0.105838
	(0.72056)	(0.16210)	(14.5133)	(0.66378)
	[0.15472]	[0.30607]	[-0.12931]	[0.15945]
D(PCE Inflation(-3))	-0.201785	0.288705	2.338577	1.164102
	(0.68845)	(0.15487)	(13.8665)	(0.63420)
	[-0.29310]	[1.86415]	[0.16865]	[1.83554]
D(PCE Inflation(-4))	-1.202224	-0.226860	12.96956	-1.061065
	(0.69037)	(0.15530)	(13.9052)	(0.63597)
	[-1.74142]	[-1.46075]	[0.93272]	[-1.66842]
D(Assets(-1))	-0.005120	-0.001724	-0.249223	-0.010803
	(0.01037)	(0.00233)	(0.20893)	(0.00956)
	[-0.49362]	[-0.73897]	[-1.19286]	[-1.13057]
D(Assets(-2))	0.017263	0.001944	-0.185912	0.001507
	(0.01076)	(0.00242)	(0.21678)	(0.00991)
	[1.60397]	[0.80303]	[-0.85760]	[0.15199]
D(Assets(-3))	0.016869	0.000621	-0.380661	0.022454
	(0.01067)	(0.00240)	(0.21501)	(0.00983)
	[1.58027]	[0.25847]	[-1.77045]	[2.28338]
D(Assets(-4))	0.012402	0.004549	-0.235960	-0.017405
	(0.01155)	(0.00260)	(0.23262)	(0.01064)
	[1.07383]	[1.75085]	[-1.01436]	[-1.63595]

D(Gini_Income(-1))	0.132269	0.043616	0.363281	-0.133182
	(0.16457)	(0.03702)	(3.31466)	(0.15160)
	[0.80373]	[1.17814]	[0.10960]	[-0.87851]
D(Gini_Income(-2))	0.092117	0.014269	-1.614487	-0.180187
	(0.15825)	(0.03560)	(3.18734)	(0.14578)
	[0.58211]	[0.40082]	[-0.50653]	[-1.23605]
D(Gini_Income(-3))	0.229402	-0.001815	-3.061679	-0.143090
	(0.15890)	(0.03575)	(3.20053)	(0.14638)
	[1.44368]	[-0.05076]	[-0.95662]	[-0.97752]
D(Gini_Income(-4))	0.287594	0.009510	-0.383304	0.019977
	(0.14884)	(0.03348)	(2.99780)	(0.13711)
	[1.93228]	[0.28405]	[-0.12786]	[0.14570]
C	0.001216	0.001588	0.126814	0.002715
	(0.00504)	(0.00113)	(0.10146)	(0.00464)
	[0.24142]	[1.40117]	[1.24992]	[0.58506]
R-squared	0.465672	0.471456	0.289046	0.479363
Adj. R-squared	0.214224	0.222729	-0.045520	0.234357
Sum sq. resids	0.001038	5.25E-05	0.421254	0.000881
S.E. equation	0.005526	0.001243	0.111310	0.005091
F-statistic	1.851961	1.895478	0.863942	1.956536
Log likelihood	203.0831	279.1672	49.94093	207.2691
Akaike AIC	-7.297378	-10.28107	-1.291801	-7.461534
Schwarz SC	-6.653436	-9.637126	-0.647859	-6.817592
Mean dependent	0.004194	0.004297	0.034784	0.000737
S.D. dependent	0.006234	0.001410	0.108859	0.005818
Det. resid covariance (dof adj.)		9.22E-18		
Det. resid covariance		1.82E-18		
Log likelihood		752.1425		
AIC		-26.82912		
SC		-24.25335		

A.6 Estimation of the Model Ib: VECM(1)

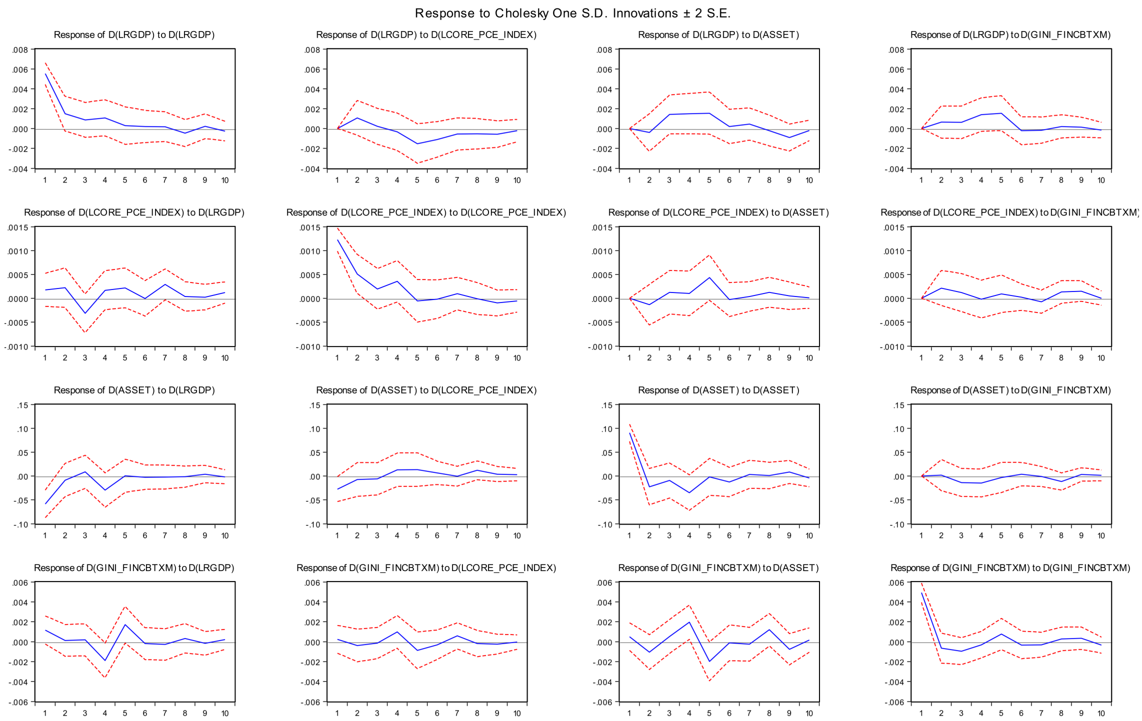
Table A.6: VECM(1) - Model Ib

Cointegrating Eq:	CointEq1	CointEq2	CointEq3	
LRGDP(-1)	1.000000	0.000000	0.000000	
PCE Inflation(-1)	0.000000	1.000000	0.000000	
Assets(-1)	0.000000	0.000000	1.000000	
Gini_Earnings(-1)	-4.818447	-4.322699	-41.18172	
	(0.54481)	(0.25185)	(2.49565)	
	[-8.84425]	[-17.1638]	[-16.5014]	
C	-6.842110	-2.121216	16.18499	
Error Correction:	**D(LRGDP)**	**D(PCE Inflation)**	**D(Assets)**	**D(Gini_Earnings)**
CointEq1	0.057320	0.030333	-1.112610	-0.004949
	(0.03682)	(0.00885)	(0.75941)	(0.03429)
	[1.55680]	[3.42582]	[-1.46509]	[-0.14432]
CointEq2	-0.260102	-0.049362	3.667528	0.096557
	(0.07715)	(0.01855)	(1.59130)	(0.07186)
	[-3.37130]	[-2.66053]	[2.30473]	[1.34372]
CointEq3	0.019343	0.001421	-0.244058	0.009031
	(0.00478)	(0.00115)	(0.09865)	(0.00445)
	[4.04431]	[1.23567]	[-2.47401]	[2.02735]
D(LRGDP(-1))	0.044800	-0.038432	-0.920885	0.073394
	(0.15501)	(0.03728)	(3.19727)	(0.14438)
	[0.28901]	[-1.03097]	[-0.28802]	[0.50835]
D(PCE Inflation(-1))	0.769400	0.089288	-10.34394	-0.012687
	(0.61520)	(0.14794)	(12.6889)	(0.57298)
	[1.25065]	[0.60354]	[-0.81520]	[-0.02214]
D(Assets(-1))	-0.023422	-0.004733	-0.042788	-0.019660
	(0.00845)	(0.00203)	(0.17430)	(0.00787)
	[-2.77166]	[-2.32892]	[-0.24549]	[-2.49790]
D(Gini_Earnings(-1))	-0.059031	-0.006009	1.344757	0.099886
	(0.13875)	(0.03337)	(2.86177)	(0.12923)
	[-0.42545]	[-0.18010]	[0.46990]	[0.77294]
C	0.001898	0.004257	0.082681	0.001314
	(0.00280)	(0.00067)	(0.05783)	(0.00261)
	[0.67706]	[6.31399]	[1.42977]	[0.50309]
R-squared	0.475785	0.357965	0.194854	0.470291
Adj. R-squared	0.396013	0.260264	0.072332	0.389683
Sum sq. resids	0.001125	6.51E-05	0.478711	0.000976
S.E. equation	0.004946	0.001189	0.102014	0.004607

F-statistic	5.964322	3.663885	1.590361	5.834309
Log likelihood	214.4026	291.3595	50.96967	218.2412
Akaike AIC	-7.644539	-10.49480	-1.591469	-7.786711
Schwarz SC	-7.349875	-10.20013	-1.296805	-7.492047
Mean dependent	0.004590	0.004298	0.033308	0.001006
S.D. dependent	0.006364	0.001383	0.105916	0.005897
Det. resid covariance (dof adj.)		5.19E-18		
Det. resid covariance		2.73E-18		
Log likelihood		785.4468		
AIC		-27.46099		
SC		-25.84034		

A.7 Impulse response functions of the Model Ia: VAR(4)

Figure A.4: Impulse response functions of the Model Ia: VAR(4)



A.8 Impulse response functions of the Model Ib: VECM(1)

Figure A.5: Impulse response functions of the Model Ib: VECM(1)