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Master's Thesis

MSc. International Economics

How does unconventional monetary policy affect income inequality? Evidence from the United States

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Abstract

This thesis examines the effect of unconventional monetary policy on inequality in the United States between 1996Q1 and 2013Q3. A vector autoregressive model (VAR) is applied to isolate this effect. The last decade, inequality became at the heart of monetary policy and cannot longer be seen as a side effect. Instead, we have to pay attention on the income distribution consequences when central banks are forced to conduct unconventional monetary policy as not all households are affected equally.

Key words: Monetary Policy, Quantative Easing, Income Inequality, VAR model, VECM, Gini coefficient, Monetary Base, Unconventional Monetary Policy, Monetary Transmission Mechanism

JEL classifications: E01, E21, E50, E58, E65

Preface

During the first month of writing this paper, it was hard for me to formulate a small and interesting research question. From the beginning I knew I wanted to relate my topic to the work of Piketty (2014) combined with Quantitative Easing. The area of Quantitative Easing (monetary policy) was an unknown and therewith a challenging area for me. Professor Dr. C.G. de Vries advised me papers to read, which would help me to understand the area of monetary policy to an extent that was necessary for writing this paper. Furthermore, I am very grateful for his help, suggestions and supervision during the writing process.

In the midst of developing my model, I had help from Jon Frost of DNB. He explained some useful background techniques he used in his paper (Saiki and Frost, 2014) for which I am very thankful.

Furthermore, I want to thank my partner who encouraged me and who was a valuable sparring partner.

Above all, I want to thank my parents, family for their ongoing support and interest during my work, especially during my studies. They have supported me in a way that was comfortable and encouraging

1 Introduction

"QE was a ‘massive gift’ intended to boost wealth"

Dallas Fed President R. Fisher (2014)

The intent of this paper is to shed light on the implications of unconventional monetary policy applied by the Federal Reserve since the escalating global financial crisis in 2008. More specifically, I identify what the consequences of the Quantative Easing (QE) program are for the U.S. households' income distribution.

For a long time income distribution effects have been globally seen as a side effect of monetary policy, instead of considering them as of major relevance. However, this view has changed markedly upon the monetary policy measures that the Federal Reserve and other central banks undertook which were, in their belief, essential during the financial crisis of 2007 to 2008 (Financial Times, 2012). European Central Bank's president Draghi even said at the International Monetary Fund on May 14th, 2015[1]: "*It has become more important that those consequences are identified, weighed and where necessary mitigated*." Remarkably, no central bank in the world has income distribution within its mandate.

The intensified attention on the effects of monetary policy on income distribution can also be traced back to the fact that income inequality has been on a rising trend in much developed economies, especially since the onset of the financial crisis in 2008. Fed president Yellen also highlight her concerns about this topic. In a speech at the Conference on Economic Opportunity and Inequality at the Federal Reserve Bank on October 17th 2014 she said : *" It is no secret that the past few decades of widening inequality can be summed up as significant income and wealth gains for those at the very top and stagnant living standards for the majority*".

Additionally, the average Gini coefficient for the OECD countries, which is a standard index to measure income inequality that ranges from 0 (equal) to 1 (unequal), has increased from 0.29 in the mid-1980s to 0.32 in the late 2000s. This has caused an active debate on searching for reasons why it is rising and it was probably sparked with the pioneering work of Piketty and Saez (2003) on income inequality, more recently with Piketty’s *Capital in the Twenty-First Century* (2014).

The idea that unconventional monetary policy employed by the Federal Reserve Bank does indeed have important implications for the income distribution, is based upon the fact that a large amount of the increase in liquidity provided by the central bank went abroad and went into increases in asset prices. Just a little part of it was used for the expansion of credit (Stiglitz, 2015). The consequence of these money flows is that the households with a high number of financial assets will benefit from an increase in the valuation of those assets, like dividends and capital gains. This is where the inequality aspect comes in. Richer

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[1] The camdessus lecture can be read on www.ecb.europa.eu : "The ECB's recent monetary policy measures: Effectiveness and challenges"

households - who in general have a more diversified asset portfolio - may benefit *more* from a larger monetary base (due to higher asset prices) compared to poorer households- who often own much less financial assets and, instead have more savings or even debts. Nevertheless, there is a general consensus that everyone had benefitted thanks to an overall boost of the economy and the prevention of a financial meltdown of the U.S. (Walker, 2014).

The main hypothesis addressed in this paper is therefore:

A higher monetary base increases income inequality due to unintended distributions effects

Although it remains difficult to quantify the precise successfulness of the unconventional monetary policy implemented by the Federal Reserve Bank, we will nevertheless try to investigate this with the help of a VAR model. With this model we can investigate the impact on an income inequality coefficient that is calculated based on household survey data. By knowing how monetary policy actions affects different segments of the population, policymakers can anticipate on it by adjusting their decisions in a more effective way. For example, aggregate economic activity might be affected by decisions in ways other than expected.

The country in focus in this thesis is the United States (U.S.). The reason for the U.S. being a suitable country of analysis is the fact that the effect of monetary easing can already be traced in the economy as the program started in 2008. This is not the case for Europe, which I preferred to investigate in the first case. The two other countries that applied unconventional monetary policy are Japan and the United Kingdom. However, Japan was the country of analysis by Frost and Saiki (2014), whereas the U.K was examined by the Bank of England (2012).

To the best of my knowledge, this thesis is the first that empirically compares the effect of unconventional and conventional monetary policy on inequality for the United States. This contribution to the literature is that existing papers can be compared with our results. Reasons why they might differ can be investigated. As such, the unintended distribution effects can better addressed by policymakers. For example, by using household data, Frost and Saiki (2014) analyzed the impact of unconventional monetary policies for Japan. It can then be compared with conventional monetary policy. Examples of countries where unconventional monetary policy has been applied are the United Kingdom, Japan and more recently, the Eurozone countries.

The results of our study show that UMP conducted in the U.S. has a positive and significant effect on income inequality- or our Gini coefficient.

The paper is organized as follows. Section 2 provides a brief literature review, which starts with a discussion of the theoretical perspectives of the distributional effects of monetary policy. Thereafter, the literature review continues with an analysis of the existing literature that paid attention on the relationship between monetary policy and the distributional effects and its empirical findings. To what extend income inequality has been increased in the U.S. will be discussed in section 3. The theoretical background of monetary policy transmission and its relationship with inequality is outlined in section 4 and 5 respectively. The VAR model, which we used as framework to investigate this relationship, is explained in section 6. After that, we will describe the data we used for our VAR model that introduces the model specification shown in section 8. This model is based on the model used by Saiki and Frost (2014). Once our model is constructed, we have fulfilled some pre-tests in section 9,10 and 11 before we can run the model. Section 12 shows the results and section 13 concludes. Future recommendations are discussed as a final part of this paper.

2 Literature Review

This section describes the existing literature focusing on the topic addressed in this paper. First, we discuss some papers that investigated this from a theoretical point of view. Second, empirical studies are explained, either income inequality related to conventional monetary policy (CMP) or unconventional monetary policy (UMP).

2.1 Theoretical evidence

Theoretical papers that investigated the relationship between monetary policy and income inequality are to a large extent based on an early work of Keynes (1924). In fact, he states that changes in money affect households differently and redistributes the wealth to undesirable outcomes. Papers based on the New Keynesian theory, made frequently use of a representative agent setting (see for example Christiano et al. 2005). However, Gornemeann et al. (2014) and Areosa and Areosa (2011) argue that the distributional effect of monetary policy will be overlooked when the analysis will be in such a representative-agent setting. One of the papers that did not make use of a representative-agent setting is the paper of Gornemann et al (2014). These researchers build a dynamic stochastic general equilibrium (DSGE) model in the New Keynesian framework. A new feature in this paper is the fact that they have incorporated household heterogeneity based on labor income, employment status and potential workforce. The conclusion they made is that contractionary monetary policy leads to an increase in, among other things, income heterogeneity. However, in their paper they only look at the yield on financial assets, not on current assets. I think that is a shortcoming of their paper as it excludes the incentive of households building leverage.

2.2 Empirical evidence on the effects of CMP

A large share of the empirical papers in the field of monetary policy and inequality identified different channels through which monetary policy is able to affect unemployment, output and inflation. They suggest that inequality will subsequently respond to these variables as households are all affected differently because of their income resources (see for example Glover et al. 2011). One of the important papers that provided an estimation of this relationship is the paper of Romer and Romer (1998). They analyzed the relationship between expansionary monetary policy shocks (lower interest rates) and aggregate demand. The study shows that if low income-households are net debtors, inflation will *positively* affect the income distribution. This effect is though temporarily. Subsequently to the paper of Romer and Romer (1998), different studies have focused on the channels by which CMP is able to affect income inequality. For example, Doepke and Schneider (2006) quantitatively assessed the effect of inflation on the redistribution of nominal wealth. They found that especially the middle-class gain from inflation as their mortgage debt lowers in value. However, there are also papers that found a *negative* effect of inflation on the income distribution (see for example the paper of Eros and Ventura (2002), Easterly and Fisher (2001).

A comprehensive empirical study based on the paper of Romer and Romer (1998) is the paper of Coibion et al. (2012), which has focused on contractionary monetary policy shocks instead of expansionary shocks. They conclude that interest rate shocks - identified by using an approach of Romer and Romer (2004) - have a statistically significant impact on inequality. Specifically, by using household survey data for the United States over the period 1980-2008, they found that when a central bank lowers the policy rate, income inequality increases across households. The paper described five different distribution channels through which monetary policy affects inequality: i) the income position channel; ii) financial segmentation channel; iii) savings redistribution channel; earnings heterogeneity channel; and v) portfolio channel. These five channels will be used in our analysis as well (section 4) since it captures our belief that monetary policy has different effects due to household heterogeneity. The findings of Coibion et al. (2012) are largely in line with the theoretical findings by Gornemann et al. (2014). Other papers related to these channels are for example the paper of Heathcote et al. (2010), which paid attention to the earnings heterogeneity channel.

There are a few empirical studies that have examined the reverse relationship: the effect of income inequality on inflation. One of the papers that shed light on this is the paper of Al-Marhubi (1997) and Dolmas et al. (2000). With the help of an OLS regression both papers found, even after controlling for the economic situation like openness, a positive correlation between inequality and mean inflation.

2.3 Empirical evidence on the effects of UMP

Contrary to the papers focusing on CMP, there is a small amount of empirical evidence on the relationship between UMP and inequality. Studies of this relationship have so far solely focused on the United Kingdom (see for example the paper of the Bank of England, 2012 and Saiki and Frost, 2014). Saiki and Frost have examined the impact of UMP on inequality in Japan by estimating vector auto regression (VAR) model. Using household survey data, they found that QE (besides a positive effect on economic growth) has a negative unwanted effect on income inequality. The channel they attribute to this phenomenon is the portfolio channel: an increase in the asset prices bodes well for the high-income households that hold these assets. Lower income households hold a smaller amount of these assets and thus will the richer households benefit *more.* This resulted in a widened income gap in Japan. Besides their findings, they concluded that the effects might be larger in other economies where households may a higher percentage of their savings in interest bearing activities such as equities and bonds.

One of these economies that suites well for comparison are the United States. Watkins (2014) already presents evidence for the United States, but does not explain the mechanism behind it (e.g. the five different channels identified by Coibion et al. (2012)). The findings of these studies are yet difficult to apply on the Eurozone as the effects on the real economy of the quantitative easing program are expected to be feasible after two years as from now. Furthermore, the Eurozone countries are characterized by different tax systems and the access to financial markets is different across the countries. This makes it a challenging job to build an appropriate model for the Eurozone.

2.4 Conclusion

As we can see, research about the impact of monetary policy on inequality is not a whole new topic, although the mainstream of theoretical evidence has focused on CMP instead of UMP. Empirical papers related to CMP are about the impact of different monetary policy instruments on income inequality and conclude that households are affected in unequally due to their different income resources. A few papers have investigated the reverse relationship. Although papers focusing on UMP have been scarce for al long time, this has changed since the aftermath of the financial crisis that started in 2008. The attention on the relationship between UMP and income distribution has been intensified. A consensus finding between these papers is that contractionary monetary policy in the UK and Japan leads to a higher inequality (Bank of England (2012), Saiki and Frost (2014)). They refer to different transmission channels, while the paper of Watkins (2014), focusing on the U.S., did not. We see this as a shortcoming, and therefore we have chosen the U.S. to build on this work. The next section is about the concept of inequality, while the subsequent section provides an overview of the monetary transmission mechanism, before we link them in section 5.

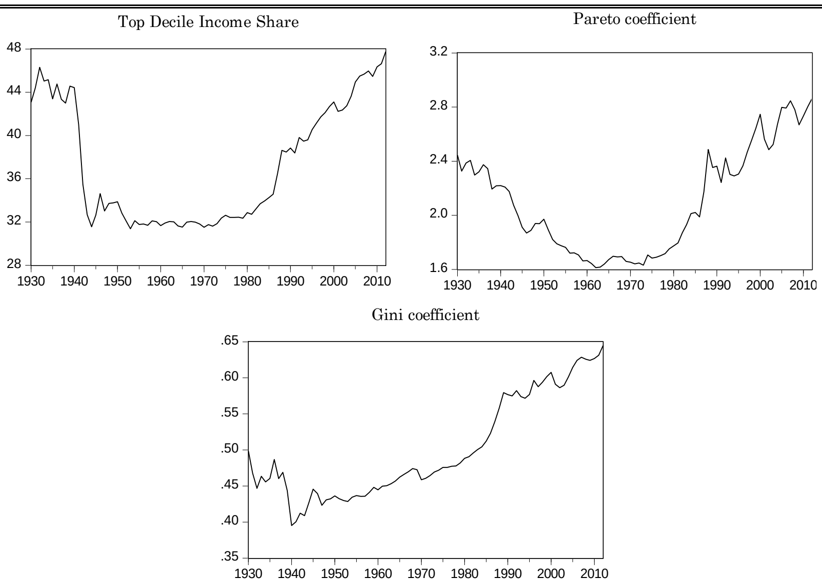
3 Has inequality increased in the U.S.?

This section discusses the widely spread debate whether income inequality has indeed increased in the U.S. First, a definition of inequality is given. Second, different factors that affect income inequality are explained.

3.1 Inequality development along different measures

Inequality has many different meanings. Therefore, it is important to be explicit about what is distributed and across whom. The recent debate has focused on inequality in two different forms. The first is *income inequality* and refers to the distribution of returns from labor and capital (Alvaredo et al., 2015). Secondly, *wealth inequality* focuses on the distribution of assets. This form of inequality embeds differences in saving behavior but also inheritances and bequests. Although the two different forms do not measure the same thing, they are interrelated. Higher income inequality adds to the concentration of wealth and in turn, higher wealth concentration exacerbates income inequality (Saez & Zucman, 2014). Both ways of inequality can be measured across and within countries. This paper focuses on *within-country* inequality: the United States.

Figure 1: Income inequality is increasing within the U.S.



Notes: (1) Share of income accruing to the top 1% of the U.S. households. (2) Inverted Pareto-Lorenz coefficient β (i.e. the inverted power from the Pareto distribution); measures the household's income above y: a higher coefficient means higher inequality (3) Gini coefficient; measures the overall income inequality: a higher coefficient means a more unequal income distribution.

Much of the debate that has focused on income inequality has looked at the dynamics of the income share accrued to the top 10%, 5%, 1% or even 0.1% (Piketty (2014), Atkinson et al. (2011)). The share of the top 1% in the U.S. economy has risen rapidly in the past few decades (see figure 1, left hand panel).

Within the U.S., income inequality seems to be rising. As becomes clear from the second panel in figure 1, there is an U-shaped time pattern of income inequality measured by the Pareto coefficient. This measure of income inequality captures the higher-income part of the distribution (Atkinson et al., 2011). To be more precise, the coefficient shows the average income of the people that have an income above a certain threshold income. For example, in 2010 the average income of household with an income above $100.000 was around $270.000, whereas this was around $170.000 in 1960. Thus, after a thinning 1950s, the right tail of the income distribution is getting fatter, i.e. the Pareto coefficient increases. However, in order to say something about the overall income inequality, the Gini coefficient is a better indicator. The similarity in the evolution the income accrued to the 1% and the income inequality suggest that the income of the top 1% is an important driver of inequality. Nevertheless, the Gini coefficient is more sensitive to changes of the middle-income group instead of the upper tail. The graph shows that the coefficient is showing an upward trend, meaning that the overall income inequality is on a rising trend as well.

3.2 Drivers of the growing inequality

Trends in the income inequality reflect a whole range of factors. One may think of technology, declining labor share and globalization. Globalization creates global opportunities for high-skilled workers whereas low-skilled workers face competition from (cheaper) foreign labor and a loss of bargaining power. Technological progress has also increased the amount of unemployed low skilled workers. However, the rapid increase at the top of the U.S. income distribution cannot be explained by exclusively the technological change and globalization. According to Piketty (2014), this phenomenon has been linked to the rapid growth of the financial sector since 1980. Furthermore, a higher rate of return on capital relative to labor has also been identified as a factor that contributed to inequality. Piketty build his theory on the assumption that $r>g$, where r is the return on capital and g refers to economic growth. This drives inequality (Piketty, 2014). Return on capital can be dividends, rents, sales of property, capital gains and corporate profits. If these are higher than the labor income, the capital share of total income increases. Since the wealth distribution is more concentrated than income distribution, inequality increases.

3.3 Conclusion

It became clear that income inequality in the U.S. has been on a rising trend in the past few decades. Different indicators are helpful to say something meaningful about this trend, where the Gini coefficient is the most used one. The rising trend of income inequality in the U.S. cannot longer exclusively be explained by the well-known concepts as technological innovations and globalization. Piketty's theory, relating income inequality to the return on capital has pointed as an important factor as well.

4 Monetary policy: theory

Before we link the previously highlighted inequality trend to monetary policy in the next section, it is important to elaborate on the main theory of monetary transmission, explained in this section.

The view that the Fed's expansionary monetary policy may have an impact on income inequality covers the traditional monetary transmission mechanism, which is recognized by many economic textbooks[2]. More precisely, it reflects how changes in either the overnight interbank interest rate (i.e. the Federal Funds Rate) or the nominal monetary supply will impact real economic variables like investment, unemployment and aggregate demand.

4.1 The Monetary Transmission Mechanism

The Federal Reserve has three different monetary policy tools formulated by the Federal Open Market Committee (FOMC). These instruments include (1) the short-term interest rate (Federal Funds Rate), (2) open market operations, which consists of buying and selling securities and (3) changing the reserve requirements of banks. The second and third instruments are equal to the term monetary base. Changes in these Federal Reserve's tools can then be passed through the real economy by six different channels as shown in the figure below. Although the channels transit the change in monetary policy each in a different way, the six channels are not mutually exclusive. In fact, the effect of monetary policy on the aggregate demand occurs with a variety of those channels. During the explanation of the various channels, we focus on the effect on households because of the reason that the focus of our paper is the monetary policy effect on households.

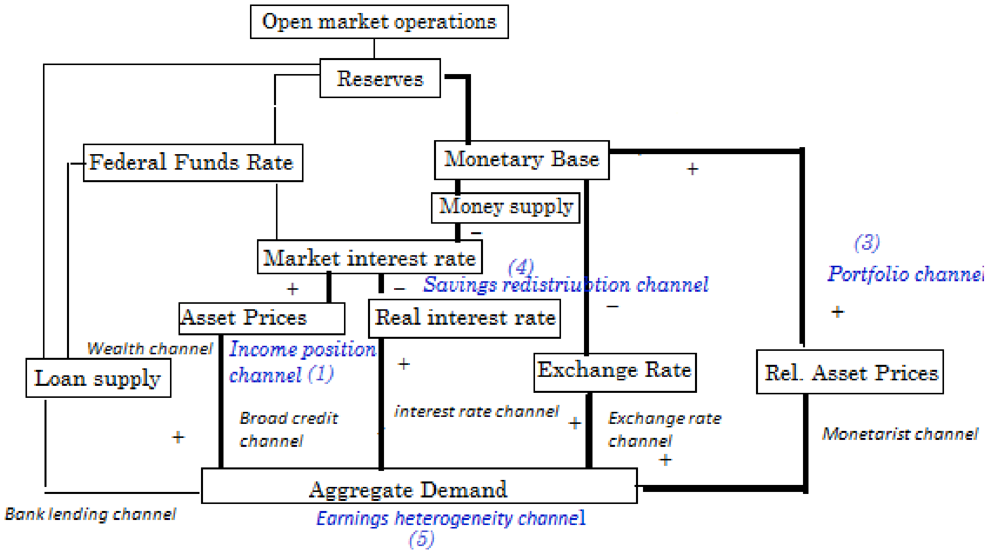
The first channel is the *exchange rate channel*. This channel builds upon the premise that a change in the interest rate has an impact on the exchange rate. For example, a decrease of the market and real interest rate will lead to a depreciation of the exchange rate. Namely, a lower interest rates is not attractive for foreigners to deposit their money in the U.S, so the demand for the currency will decline. This provokes a depreciation of the currency and hurts the economy. Furthermore, the depreciated currency influences the value of foreign assets as well. The exchange rate is important for the U.S. import and export and determines the domestic price level In turn, the net wealth of the U.S. economy declines and thereby the aggregate demand (Taylor, 1995).

The second is the *monetarist channel.* This channel is about the direct impact of changes in the monetary base on the quantity of financial assets rather than the impact of changes in the interest rate. If the Federal Reserve Bank changes the composition of the financial assets, this will have an impact on the relative value of the financial assets because since these assets are not perfect substitutes. As a result, lower

[2] See for example Walsh (2010) , Taylor (1995) who pointed out neoclassical channels, Bernanke and Gertler (1995) with the emphasize on credit channels.

or higher assets values as a result of a change in the monetary base have an impact on the households' wealth position and thereby on the consumption and aggregate demand (Bernanke & Gertler, 1989).

Figure 2: The transmission channels



Note 1: the main consequences of an increase in the monetary base (our interest) are a) a depreciation of the currency b) increase of relative asset prices c) lower real interest rates d) higher asset prices. Note 2: The blue channels, corresponding with the first 5 paragraphs in section 5, are five factors identified by Coibion et al. (2012) and placed according our believes. The financial segmentation channel was difficult to put at one position in the picture as it captures the expectations of the money supply, interest rates and inflation.
Source: Author/ Kuttner and Mosser (2002)

Researchers have long believed in the idea that a change in the interest rate, in particular, affects real variables like spending, investment, borrowing and saving. However, they started to search for extra channels that were able to explain additional effects through which a change in the interest rate affected the economy besides the "cost-of-capital" channel (Bernanke, 2007). One of these channels - the third one - is the *credit channel*. This channel shows how asymmetric information and high transaction costs creates problems in the financial markets (Bernanke & Gertler, 1995). More specifically, it demonstrates that a change in the nominal interest rate - here the FFR - is amplified by the external finance premium. The meaning of the external finance premium stands for the wedge between the firm's internal available capital and the externally raised funds via equity and debt financing (De Graeve, 2007). As long as there is no 100 percent collateralization, the wedge will exist. The smaller the collateral of the borrower, the larger the external finance premium will be. This premium can be presumably influenced by monetary policy.

In fact, the credit channel can be split into two sub-channels. The first one is the bank-lending channel, also known as the *bank-lending channel*. This view holds that the monetary policy set by the central bank influences the amount of loans supplied by the bank (Bernanke & Blinder, 1988). When many households are dependent on bank loans because there are not many substitutes for them, contractionary monetary policy has an intensified effect on the real economy. The second variant is the balance sheet channel, also known as the *broad credit channel.* In contrast to the narrow credit cannel, banks do not play the central role here. Instead, the effect of changes in the FFR or monetary base works through the payment of an external risk premium rather than credit rationing. The worse the financial position of an individual or firm, the higher the external risk premium will be. This financial position contains the value of their collateral that can be influenced by market interest rates. In turn, if borrowers have to pay a higher premium, this will reduce aggregate demand (Mishkin, 1995).

The fourth channel is the *interest rate channel*, also the conventional channel of the mechanism. This means that this channel encompasses the effect of a change in the short-term nominal interest rate into the short- and long-term real interest rates. This last transmission occurs via the expectations effect: long-term real interest rates are expected to be an average of the short-term real interest rates (Mishkin, 1996). The effect of changes in the nominal rates into the real rates is important as companies and households consider these rates. Following the IS-LM model, an increase in the monetary base will shift the LM curve downward and causes a fall in the real interest rate. If the real interest rate falls, the cost of capital will decline. This in turn spurs investment decisions by firms (Romer, 2012) and consumption decisions by either households (Bean et. al, 2002). As a result, output and aggregate demand increases. However, the effect of a change in the interest rates will be larger than implied by the consumption-spending theory (Bernanke & Gertler, 1989). They suggests that this can be explained by the belief that there are other channels involved once changes in the interest rate are made by the Federal Reserve Bank. More specifically, besides the cost of capital there are other prices in the economy that are affected by a change in the interest rate.

One of these supplementary - and also last - channel is the *wealth channel*, where the degree of household wealth determines consumption spending. A change in the market interest rate conducted by this channel spells out the impact of the change in asset prices. This means that a change in the interest rate can influence the value of assets held by households. This in turn will affect income and finally consumer spending and aggregate demand.

4.2 Conclusion

This section reviewed the traditional monetary transmission mechanism, which explains how changes in monetary policy tools - the FFR or the nominal monetary base - affect the real economy. Traditional economic theory on monetary policy identifies six different channels important in supporting this: (1) the exchange rate channel, (2) the broad credit channel, (3) the bank lending channel, (4) the interest rate channel, (5) the monetarist channel and (6) the wealth channel. We are now at the point that we have discussed the concept of inequality and monetary policy separately. The next section links the two concepts, by making use of the monetary policy mechanism discussed in this section.

5 Monetary policy and inequality

This section intertwines monetary policy and inequality. First, by following the five 'extra' channels that are developed by Coibion et al. (2012) mentioned in figure 2, the channels marked in blue. Second, we explain the distribution effects of monetary policy. Third, the concept of secular stagnation and its impact on wealth inequality is shown. Finally, we discuss the liquidity trap that forces central banks to release UMP.

5.1 Five channels linking two concepts

Coibion et al. (2012) suggested five different channels by which changes in the monetary policy tools affect households differently and thereby inequality. The first three channels lead to higher inequality, whereas the other two channels tend to move inequality the opposite way and reduce it. We tried to include the channels in the original transmission mechanism in figure 2, marked in blue.

Higher inequality

1. Income position channel: this channel is about the household different income sources. This means the differences between people that are completely assigned to income from wages and those who additionally obtain income from dividend and stocks. If expansionary monetary policy increases the value of dividend and stocks, due to higher firm profits, more than wages, then this channel will lead to a higher income inequality.

2. Financial segmentation channel: Not all people have easily access to the financial markets. Those who have faster and easier access have more information about the financial markets and can therefore anticipate in advance. As such, an increase in the monetary base will distribute to those people who are most closely connected to the financial markets instead of household that do not participate so actively in these markets.

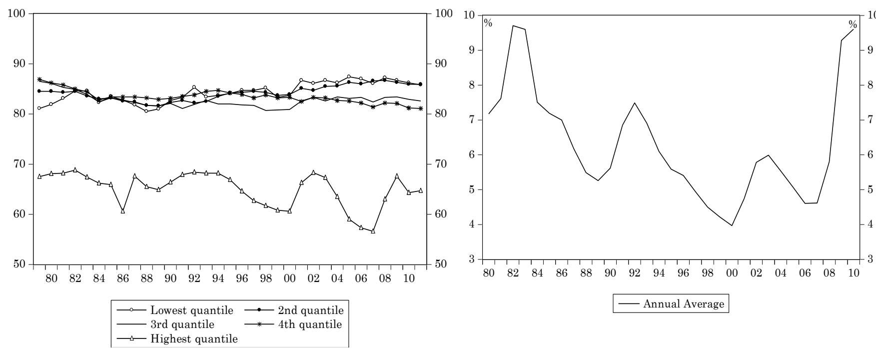
3. Portfolio channel: inflationary actions by the Federal Reserve will have a greater impact on people with a lower income compared to the higher income people that generates income from more income sources. Low-income household tend to have more cash in hand compared to higher income households who often own a diversity of financial assets.

Lower income inequality

4. Savings redistribution channel: low market interest rates as a result of an increase in the monetary base are favorable for borrowers. If we assume that low-income households are in general lenders whereas richer households are savers, then a lower interest rate will hurt the higher income households and benefit the borrower. As a consequence, the inequality gap will reduce.

5. Earnings heterogeneity channel: lower income groups often suffer from unemployment. As can be seen from the graph below, earnings from jobs represent the largest share of income for low-income households. If unemployment falls, then an increase in the monetary base will have a positive impact on income inequality. However, the unemployment rate has been on a rising trend from 2007 onwards up to almost 9%.

Figure 3: Labor income & Unemployment



Notes: (1) Labor income as share of total income. (2) Annual average unemployment rate from people above 16 years old.
Source: Data obtained from www.irs.gov (International Revenue Service)

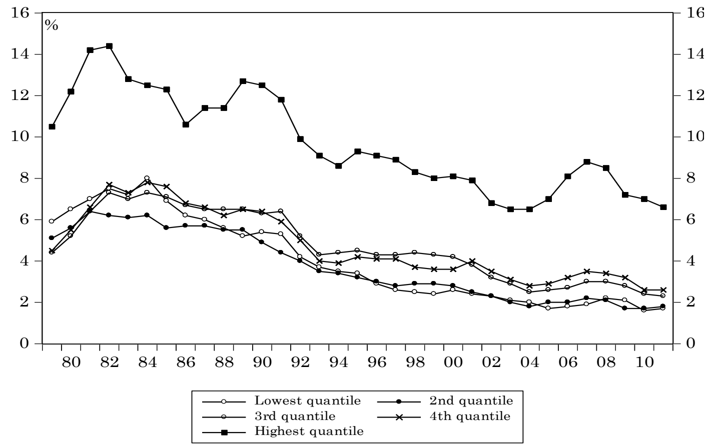
5.2 Distributional effects of monetary policy

The objective of the central bank monetary policy is macroeconomic stability - typically formulated as an inflation objective and exchange rate stability or unemployment reduction (Federal Reserve, 2015). Macroeconomic stability, in turn, bodes well for distributional outcomes as it helps to reduce the risk of large shocks to income and wealth redistribution. In particular, according to Carpenter and Rodgers (2014), promoting sustainable growth contributes to a reduction of unemployment and inequality.

This said, monetary policy might have a more direct distributional effect by influencing the yield curve and asset prices. However, given the *heterogeneity of households*, the impact of an increasing yield curve and asset prices will affect them differently and in turn, the income and wealth distribution. Two main types of household heterogeneity can be distinguished:

1. Income source heterogeneity: expansionary monetary policy might increase redistribution from the low-income to high-income households through dividend and capital gains (which have the largest contribution in the highest quintile are mainly the income source of high income households). On the other hand, if monetary policy is effective not only related to the inflation target, but also to reduce unemployment, then this will affect low-income households mostly.

Figure 4: Capital gains by income group



Source: Data obtained from www.irs.gov (International Revenue Service)

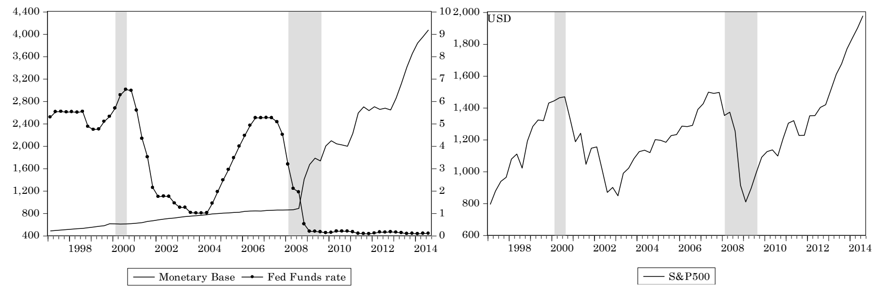
2. Balance sheet heterogeneity: this relates to the size and composition of household balance sheets. In essence, the portfolio of households is more diversified of high-income households compared to low-income households. High-income households have portfolios that contain mostly financial assets. The portfolio of low-income households consists of more housing wealth and pensions. Expansionary monetary policy (now prominent among these is quantitative easing) has mainly an effect in two ways when taking into account balance sheet heterogeneity. First, by the value of financial and non-financial assets. Financial assets contain a larger share of the portfolio of high-income households, whereas non-financial assets contain a larger share of low-income household's portfolio. Secondly, expansionary monetary policy tends to favor households with positive duration gaps- that is, households whose assets have longer maturity than their liabilities. These assets are often long-term bonds or mortgages. Contrary, households whose savings are short-term deposits tend to lose out. However, these duration mismatches are not captured by the net wealth positions of households. It is therefore important to take into account gross financial positions when one analyzes the distributional effects of monetary policy.

Income and wealth heterogeneity also have an *intertemporal dimension*, as they evolve over time to reflect the life cycle of households and population dynamics. It is therefore likely that this will influence the saving patterns of households as well. As a result, these developments may affect future distributions. For instance, very low interest rates since 2008 have affected pension funds, for which the duration of liabilities is higher than that of assets (Bank of England, 2012). This requires higher pension contributions (e.g. higher savings) or cuts in the pension benefits or both. This financing burden is likely to affect future generations, which would tend to widen future wealth distribution.

5.3 The distributional effects since 2008

Since 2008, large economies, like the U.S., the U.K., Japan and the Eurozone, started to use unconventional policies, which may have had a larger and more persistent distributional effect than conventional ones. The mainstream of micro-founded macro-models assumes that conventional monetary policy works first and foremost through *intertemporal substitution effects*. Lower interest rates stimulate aggregate demand by making current consumption and leisure cheaper relative to future consumption and leisure. As a result, households bring consumption forward and work less. *Wealth effects* arise only indirectly in the general equilibrium. As aggregate demand increases with lower interest rates (expansionary monetary policy), so does spending and as a consequence, households income.

Figure 5: MB, FFR and S&P developments



Notes: (1) Monetary Base and Federal Funds Rate. (2) S&P500, Shaded areas are U.S. Recessions
Source: data from Federal Reserve Bank of St. Louis

Since policy rates have reached the zero-lower bound (see the left hand graph in figure 5 from 2008 onwards), monetary transmission has had to rely more on *wealth effects* instead of the *intertemporal substitution effects*. In essence, since 2008, the value of financial assets has increased significantly, reflecting large capital gains on equities and bonds (see right hand graph in figure 5). These values are increased because of ultra-low, if not negative, interest rates that supported investors risk appetite. However, the ultra-low interest rates have reduced interest income, the flip side of the valuation gains. This involves a significant transfer of income from creditors to debtors.

5.4 Secular stagnation and wealth inequality

The reduced interest income brings us to a much deeper concept of *secular stagnation,* popularized by Hansen in the 1930s. The concept has been on the background for a while but has returned to prominence by L. Summers (2014). He thinks we have now ended up in a period of secular stagnation. In fact, this means that the funds available by loans exceed demand for investments (Summers, 2014). Normally, central banks are then forced to lower real interest rates in order to stimulate demand for investment. However, when interest rates are already at the zero-lower bound, problems cannot longer be solved with conventional monetary policy by just lowering the interest rates and the economy is said to be stagnated without fiscal stimulation (Teulings, 2014). The consequence of this phenomenon is that consumers are seeking for attractive saving locations in foreign countries. So, reduced investments rates together with the reduced saving rates hampers economic growth and consequently, does not reduce the unemployment rate which is one of the five factors identified by Coibion et. al (2012) that *if* unemployment diminish, UMP bodes well for income inequality.

5.5 Liquidity trap

Due to the zero-lower bound, monetary policy is seen as ineffective as interest rates cannot be set lower. This is known as the *liquidity trap*. This view is formulated according to Keynesian economic theory (Keynes, 1936). In fact, it means that aggregate demand is stagnated and spending is below a certain level that is needed to prevent cyclical unemployment. Not only the U.S. economy is seen as being in a liquidity trap, but the Eurozone and the U.K. also face the same macroeconomic problem (Krugman, 1998). Though, it might be the case that monetary is still effective when policy interest rates have reached the zero-lower bound. In this case, UMP is seen as a solution.

It works as follows: when interest rates cannot be set lower, the economy need a stimulus in the form of money in order to prevent stagnation and create demand. This is what happened in Japan in 2002, the U.S. in 2008, the U.K in 2008 and more recently, the Eurozone in 2015. Central banks started to use UMP instruments by large asset purchases. These purchases, or better known as quantitative easing (QE), have increased the amount of portfolios that consist of riskier assets. Although the QE also tried to increase inflation, it remained below their target level as households did not increase their spending, but rather kept saving their money.

While QE is one of the few ways to get out of stagnation, Keynesian economists stress that it is just a rough way of stimulating the economy and think that fiscal policy will be more effective. Their argument is based on the view that fiscal policy is, unlike QE, able to target those households that are important for economic recovery. These households have namely the highest marginal propensity to consume. QE instead, will benefit the higher income households *more* by and thus lead to a higher income gap.

5.6 Conclusion

This section has linked two concepts, namely inequality and monetary policy, to the relationship that is of main interest in our paper: *the effect of unconventional monetary policy on inequality*. The five 'extra' channels identified by Coibion et al. (2012) have supported the relationship. In fact, the channels can be separated by those contributing to higher income inequality (income position channel, financial segmentation channel and the portfolio channel) and those contributing to lower income inequality (savings redistribution channel and earnings heterogeneity channel).

Due to the concepts of income source heterogeneity and balance sheet heterogeneity, monetary policy has distributional effects that are likely to increase the income gap. Namely, the direct effect of lower interest rates results in an increase in asset prices, which will benefit higher-income households more compared to lower-income households.

Due to the zero-lower bound, interest rates cannot be set lower and instead, UMP has to be conducted (liquidity trap). This means that there are no more intertemporal substitution effects induced by lower interest rates, but only the wealth effects caused by UMP.

One way how UMP can lead to lower income inequality is to decrease the unemployment rate. However, the concept of secular stagnation, which has hit the economy up until 2014Q1, has made this difficult. Since the financial crisis of 2008 the majority of the people prefer saving and lowering their debts. Furthermore, they are reluctant to increase their consumption level. Hence, UMP contributes not to lowering income inequality but widens the gap between the poor and the rich based on the theoretical analysis of this section. We investigate this in the following sections.

6 Model

The analysis in the previous sections requires empirical testing and modeling. This section introduces the model that we use to execute the empirical part of this paper. Besides explaining the model, we also pay attention to some remarks of the model.

To assess the effects of U.S. unconventional monetary policies on income distribution, we employ a Vector Auto Regression (VAR) model that has been introduced by Sims (1980) in order to estimate equations simultaneously. We have opted for this model technique because of two reasons. First, VAR models are commonly used in the empirical analysis of monetary policy issues both by academics and policy makers [3]. The basic idea using type of model is to identify the effect of a monetary policy shock (either conventional or unconventional) on other variables of interest in the model. In most cases, these variables are related to monetary policy goals, like GDP growth, inflation and the unemployment rate. (Bagliano & Favero, 1997). Second, as previous studies investigating the effect of monetary policy on income distribution employed the VAR methodology, we are able eventually to compare the results.

6.1 VAR Representations

In its simplest form, a VAR model consist of two variables y_{1t} and y_{2t} which are regressed upon previous values of both variables and its error terms. The variables might be in levels or in first differences and are assumed to be not co-integrated. If they are co-integrated, it is no longer a VAR model but a VEC model, which will be discussed after discussed the VAR representation. In equation formulation, a basic VAR model with 2 variables and 1 lag (i.e. VAR (1) for K=2) has the form of

$$y_{1,t} = c_{1t} + a_{11}y_{1,t-1} + a_{12}y_{2,t-1} + \varepsilon_{1t} \quad (1)$$

$$y_{2,t} = c_{2t} + a_{21}y_{1,t-1} + a_{22}y_{2,t-1} + \varepsilon_{2t}$$

In matrix notation, model (1) becomes

$$\begin{bmatrix} y_{1,t} \\ y_{2,t} \end{bmatrix} = \begin{bmatrix} c_{1t} \\ c_{2t} \end{bmatrix} + \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} y_{1,t-1} \\ y_{2,t-1} \end{bmatrix} + \begin{bmatrix} \varepsilon_{1t} \\ \varepsilon_{2t} \end{bmatrix}$$

Or

$$Y_t = C_{i,t} + A_i Y_{t-i} + \varepsilon_t \quad i = 1 \quad (2)$$

Where Y_t represents the model of the response time series $(y_{1,t}, y_{2,t})$ reflecting the instantaneous relations; C is a vector with constants of 2 elements; A_i is the (2x2) coefficient matrices and ε_t is an unobservable white noise vector process of length 2 where the covariance of the error terms are equal to σ for all t=s and 0 otherwise.

[3] See for example Chen et. al. (2015), Saiki and Frost (2014), IMF (2013b), Coibion et al. (2012), Bernanke et al. (2002) and Dale et. al. (1995).

6.2 Remarks

VAR models are an appealing tool for economic analysis, because they are relatively easy to apply. However, they have also limitations that we have to bear in mind. One of these is that the impulse response functions may lead to a misleading interpretation if one of the included variables is highly persistent. Another disadvantage of VAR models is that without any modification, standard VAR models miss nonlinearities, conditional heteroskedasticity, and drifts in the parameters. Although we could consider other models, they have limitations as well. For example, DSGE models do not often fit the data well, which makes the framework not suitable for an empirical analysis[4].

On the other hand, when it is yet difficult to interpret the causation and correlation in a VAR model, it will be even more difficult in a simple equation model. We will therefore choose the VAR model, which will fit the data and can state properly something about the causal connections (Bullock, 1994).

6.3 Conclusion

The model that will be used for the empirical analysis is a VAR model. Although the model knows some deficiencies, it is frequently used in previous papers. So, we have opted for this model as well. Furthermore, it allows us to compare the results eventually.

[4] An example of a paper that makes use of a DSGE model to investigate the distributional consequences of monetary policy is the paper of Gornemann et. al (2014).

7 Data

This section introduces the data that will be used in the model. Although much of the data comes directly from a foreign database, we generate the Gini coefficient ourselves which will be explained in the first four paragraphs. Thereafter, we explain which variable we use for measuring UMP. Thereafter, we discuss the other variables used for the model.

7.1 Available measures of inequality

There are several databases that provide standard measures of inequality: the Gini coefficient, Theil index, or income groups by percentiles. Nevertheless, we will construct an inequality coefficient based on income variables from the Consumer Expenditure Survey (CEX) that are provided by the Bureau of Labor Statistics (BLS). The reason for this is two-fold. First, in order to examine the effects on income inequality in a VAR model, it is necessary to incorporate data on a higher frequency than yearly data, which are employed by Piketty and Saez (2013). When yearly data is used, we have not enough data points in the model since the sample period covers 16 years (1997-2013). Furthermore, as we expect that the effects of an UMP shock (i.e. asset purchasing) are visible within less than a year, it is necessary to incorporate an inequality variable at a higher frequency.

7.2 Consumer Expenditure Survey (CEX)

The CEX is a comprehensive data source of the U.S. household consumption and income and consist of two different kinds of surveys: a diary survey and an interview survey. Since the interview survey provides more detailed information on the households' income and expenditures compared to the diary survey, the first one will be used. The interview survey is a monthly-rotated panel where the included households are representative for the U.S population. This means that employees as well as non-employees are included. The survey started in 1997 where each household is interviewed once per quarter (equals three months). Hence, we are able to create an inequality coefficient on a quarterly basis.

7.3 The Gini Construction

The income database of the CEX consists of different income sources varying from income from dividends to income from pensions and salary income. However, we assume that not all these different income sources are relevant to trace out the effect of UMP on inequality. Instead, it will be more interesting to look at those income variables that are linked with the channels through which an increase in the monetary base might impact households differently. These channels are the as discussed in section 4.1. The variables of the survey that are summed up as the income variable are listed in the table below. Although the savings redistribution channel is an important determinant for determining the effect of an increase in the monetary base (see section 5.1), we did not include a variable for it. The reason for this is that the surveyed people would then not be the same as for the savings amount per household. However, we still included a variable that is connected with the channel suggesting lower inequality. This variable is income from wages related to the earnings heterogeneity channel.

Table 1: Income variables for Gini construction

Name CEX	Definition	Related channel
INTEARNM	Income from interest on saving accounts or bonds	Portfolio channel
FININCX	Income from dividends, royalties, estates or trusts	Portfolio channel
FINCBTAX	Income before taxes of interest, royalty, other income, welfare	All channels
FSALARTM	Income of wage and salary before deductions	Income-position/ Earnings-heterogeneity channel

Source: Consumer Expenditure Survey (CEX) provided by the Bureau Labor of Statistics (BLS)

7.4 Measuring inequality

The inequality coefficient can be measured in different ways. In this paper, there will be focused on two different kinds of inequality measures that are most widely used. The first one is the Gini coefficient, which is a conventional method of measuring inequality in almost all empirical work (Atkinson, 1996). The coefficient is measured according the formula:

$$Gini = 2\int_0^1 \left(x - f(x)\right) * dx$$

Where
x = represents the complete equality line
f (x) = represents the Lorenz function describing the distribution of wealth

First the total income of each household is calculated based on the income sources in table 1. After the calculation of the income per household, we divided the total number of households in the specific sample by 10 in order to create percentiles. As such, the total sum of income of the households in each group represents 10% of the total income of all households in the sample. The distribution example calculation is attached in Appendix B, figure 1.

7.5 Variables for monetary policy shocks

As an UMP tool, we look at the monetary base as indicator for monetary base expansion after asset purchasing (quantitative easing). The reason why we did not include the M3 monetary aggregate is that as of March 2006 the Board of Governors of the Federal Reserve System ceased the publication of this indicator as it appeared to provide no additional information that was not embodied in M2 (Federal Reserve, 2006). It might therefore be better to use an indicator that is published throughout the analyzed period, which is from 1997-2013. Thus, we take the M1 and M2 together as the monetary base. The period of UMP is defined as the period starting after the collapse of the Lehman Brothers on September 2008 until June 2013 (Rogers et al., 2014).

7.6 The model variables

The data entering our model include 6 different macroeconomic variables: the Gross Domestic Product (GDP), the Consumer Price Index (CPI), the Monetary Base (MB), the S&P500 index (S) and an income inequality coefficient (Gini). A summary of these variables can be found in table 2. Much of the data comes from the Federal Reserve Bank. The stock prices are, however, gained from the Federal Reserve Bank of St. Louis and the Gini coefficient is constructed from the BLS survey data. Since the BLS survey data used for the Gini is not available before 1997, we will focus on the period between 1997 - 2014. For all the variables we included quarterly data (see table 2). The minimum value of the MB is very small (483.52 billion dollars 1997Q1) compared to the maximum value of 4072.61 billion dollars in 2014Q3. The reason for this is the start of the quantative easing program in 2008.

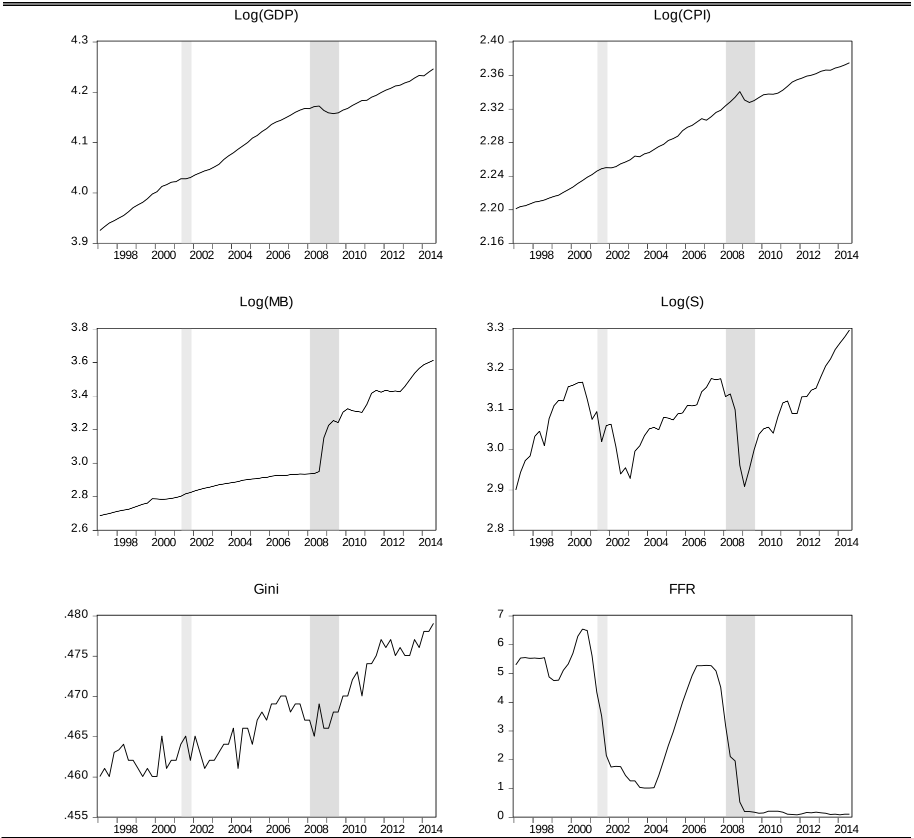
Table 2: Summary Statistics

Var.	Model	Unit	Mean	St. Dev	Min	Max	Source
GDP	Log	Billions of dollars	12957.6	2644.8	8402.1	17599.8	Fed.
CPI	Log	1982 = 100	198.7	24.5	160	237.5	Fed.
MB	Log	Billions of dollars	1341.1	1009.7	482.5	4072.6	Fed.
S	Log	Average price in last month of the quarter	1241.6	251.7	792.2	1975.9	Fed.St Louis
Gini	-	By construction	0.46	0.006	.45	0.48	Bureau Labor of Statistics (BLS)

Source: compiled by the author

Prior to the construction of our model, we transform *GDP, CPI, MB* and *S* by taking the natural logarithm. This reduces the impact of outliers as well as the often-observed increasing variance of the trending variables (Arino & Franses, 1996). Furthermore, if we run the log of *GDP* and *MB*, we can interpret them as GDP growth and MB growth respectively. This will allow us to interpret the variables in a more useful economic way. Additionally, the variable *CPI* is often treated as non-stationary on which differentiation follows. The difference of the log of *CPI* gives us then the inflation rate that has an economic interpretation as well. However, we do not apply a log transformation to the *Gini* because this rate varies between 0 and 1. Outliers will thus never be proportional to the mean value (Keene, 1995). The variables are shown in figure 6.

Figure 6: The model variables



Note: the variables GDP, CPI, MB, and S are displayed by taking the natural logarithm of the their levels. The Gini and FFR are shown in only their levels. We have added the FFR to see that the conventional monetary policy has ended in 2008. (2) The shaded areas are U.S. recessions of the early 2000 and 2008.
Source: the data used for each variable is listed in table 2.

7.8 Conclusion

The variables that we use in our model are U.S. GDP growth, U.S. inflation, the Fed's monetary base, S&P500 and the Gini coefficient calculated for U.S. households. All these variables will be included on a quarterly basis. However, since data for the Gini coefficient is only available on a yearly basis we have constructed the coefficient ourselves with quarterly data from the Consumer Expenditure Survey (CEX). The data of all the other variables are obtained from either the Federal Reserve Bank of the U.S. or Federal Reserve Bank of St. Louis.

8 Model Specification

In this section we apply our variables on the standard VAR model introduced in section 6. This will result in the VAR model on which we will build our empirical tests. Subsequently, the model will be extended with the variable S&P500. With these two models, we investigate what role the monetary base and the S&P500 have in the pass through of the increase in the monetary base.

8.1 Baseline model

For our first VAR model specification, the vector A consist of four variables *GDP, CPI, MB and the Gini* coefficient so that the model specified in (2) becomes

$$Y_t = C + A_t \qquad t = 1, \dots, T \tag{3}$$

And where A_t = [Log $GDP, LogCPI, LogMB, Gini$]

Since we only included a small amount of variables, the model is kept tractable. Furthermore, because of the short sample period it is better to restrict your model with fewer variables. The model in (3) describes all variables in their levels. However, once we applied some econometric tests, it might be the case that we use the first differences instead of the level variables in the model[5]. The model described in (3) is therefore just to describe which variables are included. As a comparison for the performance of our model, we apply the Cholesky ordering applied by Saiki and Frost (2014). The Cholesky ordering makes assumptions about the informational orderings about the monetary policy shocks and is frequently used in the empirical examination of the transmission of monetary policy shocks[6]. It is important that the ordering is correctly defined, as this will affect the outcome.

I arranged GDP growth as first, the price level second, then the monetary base and finally the Gini coefficient. This ordering reflects the belief that the Federal Open market Committee (FOMC) makes decisions according its "dual mandate[7]" (Federal Reserve, 2012). We decided to include the inflation rate (*LogCPI)* as it has been the target of the FOMC during the sample period, although the lower output growth (*LogGDP)* was an incentive for the FOMC to increase the MB. Subsequently, the FOMC set its monetary policy; conventional or unconventional when inevitable. The unconventional policy is seen as a growth rate in the MB, which is significant larger compared to the period before 2008. The Gini coefficient is ordered last.

[5] This will depend on the presence of a cointegrated relationship..

[6] See for example Edelberg and Marshall (1996), Thorbecke (1997), Bernanke et al. (2002) , Bluedorn (2006) and Chen et al. (2015)

[7] The "dual mandate" covers the monetary policy strategy of the Fed: seeking an inflation rate of 2 percent (measured by the change in CPI) and mitigating deviations of the maximum employment.

8.2 Extended model

Our second model will be extended with the variable S&P500 (equals S in our model). So, the model in (3) becomes:

$$Y_t = C + A_t \qquad t = 1, \dots, T \tag{4}$$

And where A_t = [Log $GDP, LogCPI, LogMB, LogS, Gini$]

We are trying to show different results when incorporating this variable since we believe the S&P500 has an important role in affecting the Gini coefficient. The ordering in (4) reflects the argumentation that we expect that an increase in MB is finding its way through the increase in asset prices. Consequently, the portfolio channel passes through the higher valuable assets on the Gini coefficient.

8.3 Conclusion

We have constructed two VAR models with a shorter and an extended vector. The shorter vector is without the S&P500, the latter is with. The ordering of these variables is according to the Cholesky ordering and based on the paper of Saiki and Frost (2014).

9 Pre-testing

In this section we conduct several econometric tests before we can run our VAR model properly. As such, we make sure that we can validly undertake conclusions from our model results.

9.1 Stationarity

According to economic theory, some variables will not diverge from each other, or at least in the long run, because market mechanisms, like government intervention, will bring back the variables back together again (Granger, 1986). Examples of such variables are the interest rate on asset prices, income and expenditures of a country and money supply and inflation. While economic theory might suggest certain pairs of variables, some relationships are still not clear and have to be investigated empirically.

The first step in conducting an empirical investigation for a so-called 'cointegrated' relationship, is classifying the variables as stationary or non-stationary. If the variables are stationary, then the VAR model can be estimated in which each shock on the variables will be temporary. On the other hand, if the variables are non-stationary it means that we cannot validly undertake a hypothesis about the regression parameters and we have to transform them into stationary variables. This can either be done by differencing the variables or to look for a cointegrating relationship. In both cases we need to test the lag length of the variables that is necessary to let them become stationary. The Augmented Dickey Fuller test (ADF) is central for testing this. After performing this test, we can identify those variables that can form a stationary relationship. If a cointegrated relationship exists, the VAR model requires the inclusion of a vector with cointegrated residuals. This is also known as a Vector Error Correction model (VECM).

9.2 Non-stationary variables by theory

Looking at the time series in more detail, we have included a variable that is assumed to be non-stationary by theory: the S&P500. According to the stock Efficient Market Hypothesis (EMH) proposed by Fama (1970), stock prices follow a random walk with a drift. If we assume that the EMH holds, then the stock prices in our model should be characterized by a random walk and are non-stationary. However, a large body of literature that investigated this assumption found no clear consensus about the stationarity of stock prices. We will therefore still employ a stationarity test to be sure whether we can validate the EMH (see section 9.3). This test will also be applied on the other variables.

9.3 Augmented Dickey Fuller Test

The most basic test to detect the stationarity of the variables is the Augmented Dickey Fuller test (ADF) [8], introduced by Dickey & Fuller (1979). If the variable appears to be integrated of order d, it is said to be

[8] The KPSS test has been examined as well, but as the sample size is not very large the ADF test will fit better (Hobijn et al.,2004).

I (d). Stationary variables are thus designated as I (0). After the classification, the variables can be turned into a stationary process by differencing.

However, the ADF test assumes that the variables are not bounded, i.e. the variation is limited (Cavaliere, 2005). If a variable is indeed bounded, it is prevented to drift apart from the mean by its bounds. Consequently, the ADF test might lead to a wrong conclusion that the variable doesn't walk randomly, while the mean reversion is due to its bounds. In our model, the *Gini* coefficient is always between 0 and 1 and can therefore never walk randomly. However, it might be the case that the Gini coefficient only contains a trend and drift locally (which we have observed from figure 6) while it is stationary in the long run. Theoretically, the Gini coefficient should thus be treated as a stationary variable. Nevertheless, we still apply the ADF test for the *Gini* variable.

Table 3 Results from the Unit Root Test (ADF)

Variables	In Levels		In first differences	
	ADF (i)	ADF(ti)	ADF(i)	ADF(ti)
GDP	-1.518 (1)	-1.947 (2)	-3.277 (1)	-5.009*(0)
CPI	-0.599 (0)	-1.834 (0)	-7.425*(0)	-7.389*(0)
MB	0.648 (1)	-1.589 (1)	-5.880*(0)	-6.047*(0)
S	-1.765 (1)	-2.161 (1)	-6.597*(0)	-6.557*(0)
Gini	0.277 (2)	-2.359 (1)	-8.926*(1)	-8.970*(1)

The Dickey Fuller test shows that all the variables are non-stationary and I (1). In the test we allowed for an intercept and trend for the variables *GDP, MB,* and the *Gini*. The other variables *CPI* and *S* include an intercept only. Based on the Aaike Information Criterion (AIC), which will determine the optimal lag, the non-stationary variables are turned

Notes:
- The estimated equations are: $\Delta \boldsymbol{y_t} = \boldsymbol{\alpha} + \boldsymbol{\delta t} + \boldsymbol{\rho}\, \boldsymbol{y_{t-1}} + \sum_{i=1}^{p} \Delta \boldsymbol{y_{t-1}} + \boldsymbol{\varepsilon_t}$ (in level) $\Delta^2 \boldsymbol{y_t} = \boldsymbol{\alpha} + \boldsymbol{\delta t} + \boldsymbol{\rho} \Delta\, \boldsymbol{y_{t-1}} + \sum_{i=1}^{p} \Delta^2 \boldsymbol{y_{t-1}} + \boldsymbol{\varepsilon_t}$ (in first differences).
- i and ti are the test statistics with allowance for an intercept and intercept & trend terms
- * denotes the rejection of the null hypothesis for the 5% significance.
- The numbers in the parentheses are the lags included in the test. The choice of the optimum lags is based on the Akaike Information Criterion. Source: compiled by the author

into stationary variables. These optimal lags are indicated between the parentheses in the last column of table 3. Choosing the optimal number of lags is an important step since the direction of causality between the variables may depend on the number of lags that are involved. The transformed variables are displayed graphically in Appendix B, figure 7.

9.4 Conclusion

The pre-testing results applied on each variable shows that all the variables in our model are non-stationary. Fortunately, after first differencing these become stationary.

10 Cointegration Analysis

In this section we do not test our variables separately but rather test our model as a whole. What happens when our model variables are combined in one model? If our non-stationary variables then become stationary, we have a VECM instead of a VAR model. We will discuss this possibility as well as the consequences for our baseline model as well as our extended model.

10.1 VECM

We are at the point that we know that there are variables in our model that are integrated of order 1, i.e. $\Delta y_t \sim I\,(1)$. These variables may be cointegrated. This means that the variables become integrated of a lower order once they are combined. In our case, they become $I\,(0)$. It is then not longer necessary to difference the variables first because the variables become stationary after they form the relationship (Engle and Granger, 1987).

So, we cannot simply start to apply a VAR model with our differenced variables but we have to look first whether there are indeed cointegrated relationships. A well suited test to analyze a vector with > 2 variables is the Johansen Cointegration test (1988,1991). This test takes its starting point in the VAR model of order p given by (2). Let's start with the variables of our baseline model using matrix notation: $Y_t = [logGDP, logCPI, logMB, Gini]$. If the model contains a cointegrated relationship, the VAR model specified in (2) can then be transformed to a special case: the Vector Error Correction (VEC) model. This model is specified as:

$$\Delta Y_t = \Gamma_1 \Delta Y_{t-1} + \Gamma_2 \Delta Y_{t-2} + .. + \Gamma_{p-1} \Delta Y_{t-p-1} + \Pi Y_{t-1} + u_t \tag{5}$$

Where:

$\Pi = -\,(\mathrm{I} - A_1 - A_2 - .. - A_p)$(p*p matrix with the long-run parameters)
$\Gamma_j = (\mathrm{I} - A_1 - A_2 - .. - A_p)$ (short-run parameters)
u_t = vector of error terms that are i.i.d with mean 0 and variance

10.2 Baseline model

Starting with our baseline model, we include the variables in *levels* (thus non-differenced) as argued in section 10.1. In matrix terms, we analyze:

$$Y_t = C + A_t \qquad t = 1, \ldots, T \tag{6}$$

And where A_t = [Log $GDP, LogCPI, LogMB, Gini$]

The first stage to search for a cointegrated relationship before we can build the model in (5) is to find out the lag order of the model. This can be done with the lag exclusion test. According to the mere of the information criteria given by this test, we choose the lag-length of p =1 (Appendix A, table 1).

However, the result of the lag exclusion test doesn't imply that it is the most optimal lag-length. With the LM test we investigate whether there is some autocorrelation left when choosing the lag-length of order 1. The vector LM test shows that there is no autocorrelation. However, the single equation LM test shows that there is some autocorrelation left in *CPI* and *Gini* (Appendix A, table 2). Increasing the VAR model with two lags removes only the autocorrelation in *Gini*, but not of CPI (Appendix A, table 3). However, by repeating this step, we see that the optimal lag-length becomes p = 4 (Appendix A, table 4). After obtaining the optimum lag length of 4, the next step is determining the number of cointegrating vectors with the Johansen Cointegration test.

Table 5 Results from the Johansen Cointegration Test (1)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.245105	41.61236	47.85613	0.1699
At most 1	0.206725	23.05466	29.79707	0.2434
At most 2	0.110763	7.770050	15.49471	0.4903
At most 3	0.000337	0.022221	3.841466	0.8814

Notes:
- The variables are in levels in order to investigate whether the non-stationarity is removed by a cointegration equation
- Trace test indicates no cointegration at the 5% level
- * denotes rejection of the null hypothesis at 5% level
-**MacKinnon-Haug-Michelis(1999) p-values

According to the test, we find no cointegrated relationship, suggesting that the rank of $\Pi = r$ in (5) is equal to 0 (table 5). As such, a VECM is no longer required and for the baseline model we are allowed to proceed with applying the VAR impulse response function in the chapter 11. However, since there is no cointegrated relationship, the VAR model with variables in their first differences might show spurious regressions. This will result in conclusions that are almost meaningless (Asteriou & Hall, 2007). The reason for this is that the model gives no unique long-run solution. The best way to run the VAR model is then to include the level variables instead of the first differences. We will do this in the next chapter.

10.3 Extended model (incl. S&P500)

We repeated the Johansen's cointegration test for model (4). According to the SC and HQ information criteria, we start lag length p= 1 (Appendix A, table 8). Again, there remain some autocorrelation in CPI. After repeating this step we found an optimal lag length of p=4. This might be due to quarterly data, which implies that there might be a cyclical pattern during 4 quarters.

Table 9 Results from the Johansen Cointegration Test (2)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.570225	100.6990	69.81889	0.0000
At most 1	0.259175	44.96239	47.85613	0.0912
At most 2	0.197977	25.16302	29.79707	0.1557
At most 3	0.145198	10.60220	15.49471	0.2372
At most 4	0.003747	0.247755	3.841466	0.6187

Notes:
- The variables are in levels in order to investigate whether the non-stationarity is removed by a cointegration equation
- Trace test indicates one cointegration vector at the 5% level
- * denotes rejection of the null hypothesis at 5% level
-**MacKinnon-Haug-Michelis (1999) p-values

In contrast to the baseline model (6), there is one stable cointegrated equation according to the Johansen test (see table 9). This means that there is one long-run cointegrated relationship between the variables. Before we move on with the analysis, we have to choose the appropriate model, i.e. whether we have to choose for a model with or without intercept and trend. Based on the Schwarz Information Criteria (SIC) in Appendix A table 10, we continue with the model including an intercept but no trend[9]. It is important to note that Eviews automatically include the first difference of the endogenous variables. So, we did include 3 lags instead of our identified number of 4 lags. According to table 11 in Appendix A, we can specify the cointegrating equation as:

$$\underset{}{GDP} = 0.64 - \underset{(0.045)}{2.24CPI} + \underset{(0.009)}{0.099MB} - \underset{(0.013)}{0.078S} + \underset{(0.559)}{0.753Gini} + \mu_t \quad (7)$$

Where the standard errors are in the parentheses. The cointegration vector is identified after Eviews imposed an arbitrary normalization of an index 1 to the regressed variable, in this case GDP growth. All the variables are significant at the 5% level.

Engle and Granger Two-Step Method

Although the Johansen test is a frequently used method to run a VECM model, the Engle and Granger two-step methodology (1987) provides more information. The Johansen test just say something about the long run relationship whereas the Granger two step method investigates the long run *and* short run relationship. So, we will try to identify the cointegrating vector as identified with the Johansen test in (7), but this time with an OLS regression. In fact, the Engle and Granger estimation proceeds in two steps.

[9] The Akaike Information Criteria (AIC) chooses the model with intercept and trend. However, it is assumed that if AIC and SIC shows different results, we choose the model with the least restrictions.

Step 1:

First we regress GDP on MB, CPI , S and Gini - based on the vector identified by the Johansen test in (7). As such, we get the proportion of GDP that is not attributable to MB, CPI, S and Gini. This is the long-run relationship and can be written as:

$$GDP_t = c + \alpha_1 CPI_t + \alpha_2 MB_t + \alpha_3 S_t + \alpha_4 Gini_t + \varepsilon_t \quad (8)$$

In this regression, the variable GDP act as the regressor and CPI, MB, S and Gini as independent variables that will explain the short and long-term relationship. The error correction part - we will call this Q- is measured by saving the residuals of (8). In (8) we have included all the variables that we expect to be cointegrated and have sustained shocks on the long-term relationship. A shock in one of these independent variables might then 1) immediately affect GDP growth and 2) disturb the long run relationship, which results in a new equilibrium. While we expected Gini to have a significant effect on GDP in the long run, the results show the opposite (Appendix A, table 12). According to the OLS results, we can write the residual equation as:

$$Q_t = GDP_t + 0.37 - \underset{(0.051)}{1.97CPI_t} + \underset{(0.011)}{0.07MB_t} - \underset{(0.015)}{0.08S_t} + \underset{(0.56)}{0.17Gini_t} \quad (9)$$

Where the standard errors are in the parentheses.

Step 2:

The next step is to test whether Q_t is stationary and able to capture deviations from the equilibrium relationship between GDP, CPI, MB, S and Gini. According to MacKinnon (1990) we use a different critical value than used with the standard Dickey-Fuller test. According to these criteria, the residuals do not contain a unit root (Appendix A, table 13). Therefore, we are now able to estimate the short and long term effects of Gini, CPI, MB and S on GDP by including our EC mechanism - Q_t. The equation becomes then:

$$\Delta GDP_t = c + \alpha_1 \Delta CPI_{t-1} + \alpha_2 \Delta MB_{t-1} + \alpha_3 \Delta S_{t-1} + \alpha_4 \Delta Gini_{t-1} + \alpha_5 Q_{t-1} + \varepsilon_t \quad (10)$$

If this EC representation is appropriate, then our variables should be in the direction we expect. According to Table 14 in Appendix A we obtain the following estimates

$$\Delta GDP_t = \underset{(0.004)}{0.004} + \underbrace{\underset{(0.141)}{0.34\Delta CPI_{t-1}} - \underset{(0.012)}{0.02\Delta MB_{t-1}} + \underset{(0.010)}{0.03\Delta S_{t-1}} - \underset{(0.164)}{0.03\Delta Gini_{t-1}}}_{\textit{Short term effect}} + \underbrace{\underset{(0.042)}{0.24Q_{t-1}}}_{\textit{Speed of adjustment}} + \varepsilon_t \quad (11)$$

On a 5% confidence interval, only the variable S is able to have a *short-term effect* on GDP growth with a value of 0.03. This means that a shock in S will increase GDP growth in the short term by 0.03 points. The other variables appear to have no significant short -term effect on GDP. This makes sense as significant effects of an increase in the inflation rate and monetary base is expected to be traced in the economy in the long run, and less in the short-run. However, an increase in the stock prices might be according to several empirical papers traceable in the short-run (see for example Stock &Watson (2000), ECB, 2010).

The second part of (11) gives us information about the *speed of adjustment* to equilibrium after one of the variables gets a shock. As formulated in (9), Q_t consist of CPI, MB, S and Gini. If one of these variables gets a shock, then GDP growth will respond with a rate of 24% times the increase in the variable per quarter. This will continue until the shock in Q_t has no longer an effect on GDP growth.

Although we have analyzed the cointegrated equation correctly by taking GDP as dependent variable, it is more interestingly to investigate the relationship with Gini as the dependent variable. As such, we are able to say something about the short-run and long-run impact of the MB on the Gini coefficient. We will conduct the same steps as before.

Step 1:

First we regress Gini on GDP, CPI, MB and S. This will help us to get the proportion of Gini that is not attributable to GDP, CPI, MB and S. The long-run relationship can be specified as:

$$Gini_t = c + \alpha_1 GDP_t + \alpha_2 CPI_t + \alpha_3 MB_t + \alpha_4 S_t + \varepsilon_t \quad (12)$$

Where Gini act as the regressor and GDP, CPI, MB and S as the independent variables. Again, the error correction part Q is measured by saving the residuals of (12). According to Appendix A Table 21, we can write the residual equation as:

$$\begin{aligned} Q_t = Gini_t + &\underset{(0.022)}{0.32} - \underset{(0.027)}{0.01GDP_t} + \underset{(0.054)}{0.05CPI_t} + \underset{(0.003)}{0.01MB_t} + \underset{(0.003)}{0.017S_t} \end{aligned} \quad (13)$$

Where the standard errors are in the parentheses.

Step 2:

We have to check whether is stationary and able to capture deviations from the equilibrium relationship between the variables. The results are shown in Appendix A Table 22. From this table we can say that the error correction part Q does not contain an unit root. Hence, we can estimate the short- and long-term effects of the independent variables on the Gini coefficient :

$$\Delta Gini_t = c + \alpha_1 \Delta GDP_{t-1} + \alpha_2 \Delta CPI_{t-1} - \alpha_3 \Delta MB_{t-1} + \alpha_4 \Delta S_{t-1} + \alpha_5 Q_{t-1} + \varepsilon_t \quad (14)$$

After regressing (14) we obtain the following estimates (Appendix A, Table 23):

$$\Delta Gini_t = - \underset{(0.000)}{0.0004} \tag{15}$$

$$\underbrace{\underset{(0.141)}{0.12\Delta GDP_{t-1}} - \underset{(0.012)}{0.01\Delta CPI_{t-1}} + \underset{(0.010)}{0.01\Delta MB_{t-1}} + \underset{(0.164)}{0.001\Delta S_{t-1}}}_{Short\ term\ effect} \underbrace{- \underset{(0.042)}{0.33Q_{t-1}}}_{Speed\ of\ adjustment} + \varepsilon_t$$

On a 5% confidence interval, the variables MB and S have both a short-term effect on Gini with a value of respectively 0.01 and 0.001. This means that a shock in these variables will both increase the Gini coefficient in the short-term with 0.01 and 0.001 points (in line with our expectations). The variables GDP and CPI appear to have no short-run effect on the Gini coefficient. This makes sense as the effects of economic growth and inflation is expected to have an impact on the economy after about 1 year. The second part of (15) gives us information about the speed of adjustment after one of the variables in Q - as defined in (13) - gets a shock. In this case, it means that the Gini coefficient will respond with a rate of 33% times the increase in the variable per quarter until the shock has no longer an effect on the Gini coefficient.

10.4 Weak exogeneity

The final test in order to run an appropriate model including our variables is to test for weak exogeneity. As there is only 1 cointegration vector, there are at least 4 columns in the Π matrix (see equation (5)) that are equal to zero, or in other words, weakly exogenous. The Π matrix consists of speed adjustment parameters α and long run parameters β. Testing whether the variables in (7) are weakly exogenous is equal to test which of the rows in α and β are 0. Estimating the VEC model with imposing restrictions can do this. The results can be found in table 15 for α and table 16 for β. From the α coefficient, we conclude that we cannot drop any of the variables as part of the system. From the β coefficient, we conclude that $logCPI, logMB, \log S\ and\ Gini$ are all statistically significant in the cointegrated vector of (7). So, when we run the VEC model, we do not have to impose any restrictions in the model.

10.4 Conclusion

Since our variables appeared all to be integrated of the same order -I (1)- we investigated whether, once we combine the variables in a VAR model, it leads to a stationary cointegrated relationship. If this is the case, we have to proceed with a VEC model instead of a VAR model. We saw that the combination of the variables in our baseline model did not show a cointegrated relationship, so we extend our analysis in section 12 with a VAR model. However, the extended model shows indeed a cointegrated relationship with GDP growth as dependent variable. We investigated this relationship more deeply with the Engle and Granger method and conclude that only the S&P500 has a short-term impact on GDP growth whereas all the other variables only have a long-term impact.

11 Granger - Causality Analysis

In this section we investigate the relationship between the variables. One way to do this is with the Granger-Causality test, devised by Granger (1996). In the previous section we have included all the variables together in one model, but in this section we will look to the individual relationships. After this test we know which variable is important in the determination of another variable.

11.1 The Granger -Causality test

For example, if X does not appear in the Y equation of the model then X does not Granger Cause Y. However, the case becomes more complicated in our case as we have more than two variables in our model. The results have therefore to be interpreted cautiously because the results of the tests are sensitive to the amount of included variables in the model. Nevertheless, we are still able to say something about the direction between the relationships. Estimation results are shown in the table below.

Table 17 Results from the Granger Causality test

Independent Variables

Dep. Variable	**χ^2 -Statistics of lagged 1st differenced term (p-value)**				
	Δ GDP	**Δ CPI**	**Δ MB**	**Δ S**	**Δ Gini**
Δ GDP		24.51***	12.99**	40.92***	13.51***
	--	(0.000)	(0.011)	(0.000)	(0.009)
Δ CPI	2.56		20.30***	3.01	6.11
	(0.633)	--	(0.000)	(0.556)	(0.191)
Δ MB	6.50	8.92*		8.32*	11.68**
	(0.165)	(0.063)	--	(0.08)	(0.01)
Δ S	1.16	1.89	1.20		3.03
	(0.884)	(0.756)	(0.877)	--	(0.552)
Δ Gini	1.56	8.96*	3.69**	9.88**	
	(0.8157)	(0.062)	(0.048)	(0.043)	

Notes:
- ***, **, * denotes significant at 1%, 5% and 10% significance level, respectively. The figure in the parenthesis (...) denote as p-value.

The null hypothesis that is tested is "The independent variable X does not Granger cause the dependent variable Y". If there is a variable in our model that does not Granger cause any of the other variables in the model, then it have to be excluded. The results in table 17 imply that all the variables have to be included in our model. Looking to our variable of interest in more detail: CPI, MB and S all Granger Cause the Gini coefficient, whereas GDP does not show a significant result. This does, however, not mean that GDP is not able to granger cause the Gini coefficient as the result of the test is dependent of the other variables in our model.

11.2 Conclusion

Based on the Granger-Causality test, all the variables are important to include in our model. Furthermore, the monetary base granger causes the Gini coefficient positively.

12 Structural Analysis

In the previous sections we have investigated what type of model we have to apply to end up with a well-suited model. In this section we start to analyze the structure and results of these models (baseline model first, extended model second) with the help of the following three tools:

1. Model coefficient interpretation
2. Impulse Response Function (IRF)
3. Forecast Error Variance Decomposition (FEVD)

12.1 Baseline model

$$y_t = [\, GDP, CPI, MB, Gini \,]$$

Model coefficient interpretation

The results of this model can be found in Appendix A, table 6. It becomes clear that the first and second lag of inflation is able to increase the Gini coefficient significantly. This is in line with other empirical papers that investigated this relationship (see for example Beetsma (1992), Romer & Romer (1998), Easterly & Fisher (2001) and Albanesi (2006)). However, inflation also positively affects the monetary base while we expected the opposite effect. The Fed 's aim was namely to increase the inflation rate by increasing the monetary base. The reason why we found no negative relationship is because we have analyzed a time period where inflation was on an increasing trend. Only a small time period within our sample identified a (large) decline in the inflation rate from 2008Q3-2009Q2. If we had analyzed this time period we expect to find a negative relationship. However, the small amount of observations would possibly give us unreliable results. Finally, the inflation rate affects GDP growth positively and is significant as well. This is in line with economic theory and with our expectations.

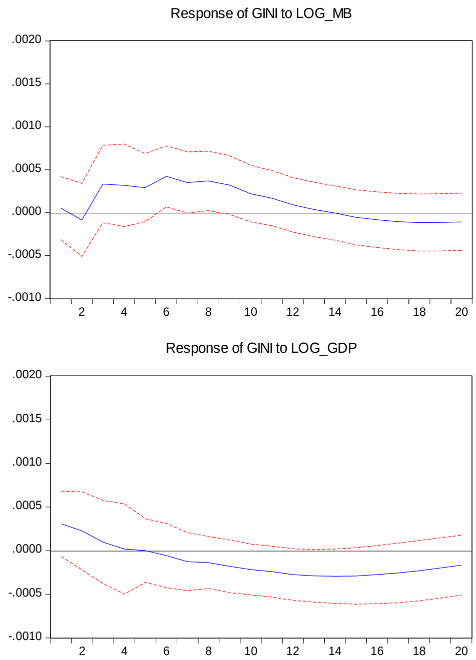
Looking at the monetary base, the results imply that it’s past value ($t - 2$) positively and significant affects the Gini coefficient. An increase of one unit monetary base results in an increase of the Gini coefficient with 0.028. Furthermore, past values van the monetary base impact the inflation rate: $t - 2$ and $t - 4$ leads to an increase of respectively 0.046 and 0.017 in the inflation rate. Again, we have investigated a longer time period than the unconventional period.

Finally it affects the GDP growth rate: an increase of 1 unit in the monetary base will increase GDP growth rate after two lags with 0.034 significantly. However, the impact on GDP growth is, according to several empirical papers that have focused on a longer time period, often visible after three years. We are unfortunately not able to include this amount of lags due to the limited observations.

Impulse Response Function (IFR)

The IFR is used to analyze the dynamic effects of our system once one of our variables gets a shock. These shocks can be either to GDP, CPI, MB or Gini. The impulse response of the Gini is represented in figure 7. We left the other responses out here, although they can be found in the Appendix.

Figure 7: Response of Gini to an 1% increase in MB and GDP



Notes:
- The red dotted line denotes the confidence bands; the blue line is the response of the Gini coefficient after a 1 percent increase in the monetary base.

We have opted for a time period of 20 quarters as you are then able to better see a pattern in the response of the variable. It seems that the MB affects the Gini coefficient positively starting after two periods and remains on an increasing trend until the 8th quarter (2 years). This means that that the effect is meaningful. The largest impact of the one standard deviation shock is between the third and sixth quarter. You see also that the response of the Gini coefficient declines after 2 years. This might be due to the delayed positive effects of QE on the economy. However, we expect a stronger increase in the Gini coefficient when the S&P500 is included as a variable. Furthermore, as we have looked at a sample period where also conventional monetary policy has been conducted (and thus not a really aggressive form of money supply), the effect might be much weaker than if we only look at the unconventional period. Again, we are not able to investigate only this time period due to the limited amount of observations. The second graph shows the response of the Gini coefficient on a 1% increase in GDP. Again, the response is significant. The thing you see in the graph is that inequality declines with economic growth until the 14th quarter. This suggest that economic growth diminishes income inequality. However, we have to be cautious as the impact of economic growth on inequality depends on the initial inequality in the country of analysis. Although interesting to analyze, this is behind the scope of the paper.

Forecast Error Variance Decomposition (FEVD)

The FEVD is an econometric tool for investigating the contribution of each variable to the variation in another variable. More precisely, what happens to the variation in variable X when variable Y gets an impulse or innovation. The focus is on the response of the Gini variable on a shock in the other variables, in particular the monetary base. To analyze the FEVD we included 16 periods, which equals 4 years. The reason for this is that we can trace out the difference between a short and long run horizon. The results are shown in Appendix A, table 19A. The model appears somewhat different in the short run: an innovation of the MB contributes less to the variation in the Gini coefficient compared to the long run (>8 periods). In the long run, the MB contributes to over 15% of the forecast error variance. The effect dies out after 11 periods. Contrary to the MB, inflation and GDP growth become even stronger in the long run. However, their contribution to the variance in Gini remains smaller in 4 years compared to the contribution of the MB (see Appendix A table 14A).

12.2 Extended model

$$y_t = [\ GDP, CPI, MB, S, Gini\ ]$$

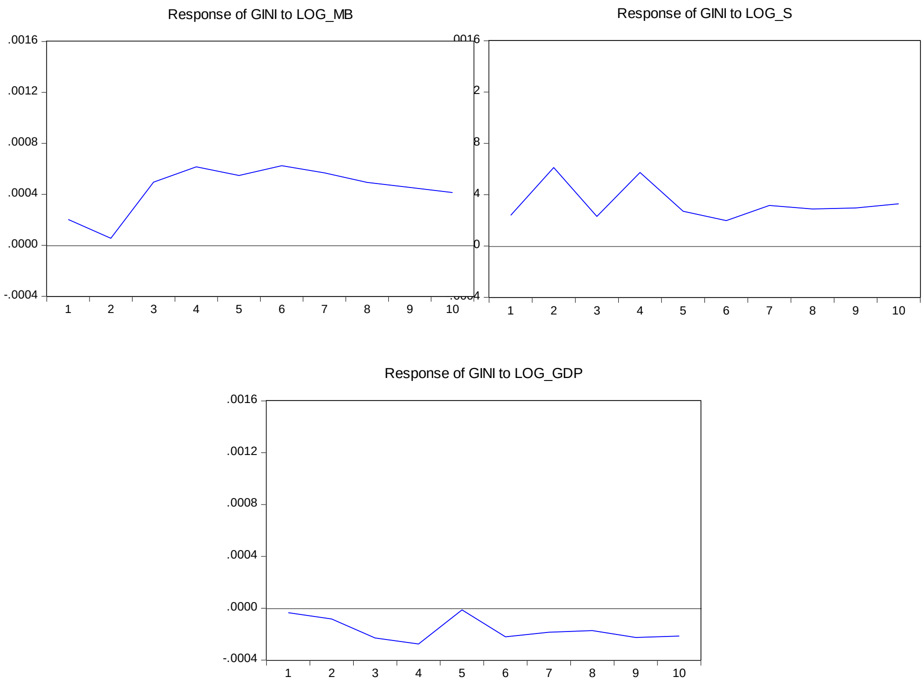
Model coefficient interpretation

The results of this model are shown in Appendix A table 14. It is in particular interesting whether the increase in MB is still significant and what the contribution of the additional variable S was. Looking at the monetary base, the results imply that, just like in the baseline model, its past value $(t-2)$ increases the Gini coefficient with 0.0019. This is much less than in the baseline model suggesting that part of the impact is attributed to S. Again, if we had analyzed this time period we expect to find a negative relationship. However, the small amount of observations would possibly give us unreliable results.

Impulse Response Function (IFR)

As with the case of the baseline model, we only highlight the response of the Gini coefficient to a 1% increase in our variables of interest. Again, it seems that the MB affects the Gini coefficient positively starting after two periods and remains positive and significant. The largest impact of the one standard deviation shock is between the second and third quarter. As we expected, the response of the Gini coefficient is now stronger compared to the model without the inclusion of the S&P500 variable (Appendix A, table 19). Just like the response of Gini on MB, an increase of 1% in S&P500 also increases the Gini coefficient in the first two quarters. However, thereafter the effect dies out and increases again in quarter three. The response of Gini to GDP is more or less the same as in the baseline model, although Gini immediately starts to response negatively.

Figure 1: Response of Gini to an 1% increase in MB, S and GDP



Notes:
- The blue line is the response of the Gini coefficient after a 1 percent increase in the monetary base, S&P500 and economic growth respectively.

Forecast Error Variance Decomposition (FEVD)

If we compare the results of the FEVD in our extended model with the results of FEVD in the baseline model, we see that the amount of variance in the Gini coefficient that can be contributed to MB has reduced. In the baseline model, the highest percentage was 20% whereas in the extended model the highest was 16%. We think that the reduced percentage is caused by the inclusion of the S variable. However, just like in the baseline model, the effect of MB dies out after 11 periods whereas inflation and GDP become stronger in the long run (Appendix A, table 19B).

12.3 Conclusion

In this section we have interpreted the results of our models build in the previous sections. We can conclude, with the help of three sub analysis tools, that the MB has a positive and significant influence on the Gini coefficient. The effect appears to be stronger in the extended model, when the S&P500 is included. Furthermore, part of the variance in the Gini coefficient that was first only explained by the MB (20%), is now also explained by the S&P500. This means that a part of an increase in the MB went into the S&P500. This resulted in a variance of 16%. Finally, S&P500 appeared to have significant and positive effect on the Gini.

13 Conclusion

In this paper we have examined how unconventional monetary policy affects income inequality in the U.S. Over the past few decades research on conventional monetary policy (CMP) and income inequality made clear that households are affected differently due to their income resources. It is only recently that unconventional monetary policy (UMP) and income inequality have been addressed as an important topic on the agenda. Studies of the Bank of England (2012) and Saiki and Frost (2014) have shown UMP unintendly increases income inequality in respectively the U.K and Japan. Based on the transmission mechanism, and in particular the portfolio channel, they collected evidence for this by empirically testing using a VAR model. Their methods and findings may also be applicable on the U.S. as this country also started with UMP in 2008. However, this was never investigated in a comparable way. This gave us the opportunity to contribute on the existing literature, discussed in section 2.

Section 3 showed that U.S. income inequality has been on a rising trend in the past few decades, while section 4 elaborated on the traditional monetary policy tools used in the U.S. Coibion et al. (2012) added five extra channels, explained in section 5, which links monetary policy with income inequality. Due to this link it became clear how monetary policy could contribute to changes in income inequality. The current UMP faces secular stagnation and liquidity trap whereby the saving redistribution channel and the earnings heterogeneity channel are not meaningful in the context of income inequality. Other channels are thus more important in the pass through of UMP (especially the portfolio channel).

Section 6 introduced the VAR model that has been used for our empirical analysis. The reason for using such a model is that we are then able to compare our results with Bank of England (2012) and Saiki and Frost (2014). The variables and data that we used; GDP growth, inflation, monetary base, S&P500 and a Gini coefficient, are explained in section 7. Section 8 constructed two VAR models including our variables and according to the Cholesky ordering. In section 9 we conducted several pre-test related to our variables individually. The outcome showed that all our variables are non-stationary. However, they became after first differencing. Section 10 shows what happened with the variables once they were combined in our VAR models. The model without the inclusion of the variable S&P500 appeared to have no cointegrated relationship, so we proceeded with a VAR model. However, the model in which S&P500 was included showed a cointegrated relationship. Consequently, we applied a VEC model instead of the VAR model. This type of model required a more in-depth analysis, which have been paid attention on in this section as well. The final test - Granger Causality- is described in section 11, where we investigated relationships between the variables separately. As all the variables are important in explaining each other, we have to include them all.

In section 12 we have interpreted the results of our models build in the previous sections. We can conclude, with the help of three sub analysis tools, that the MB has a positive and significant influence on the Gini coefficient. This means that regarding our main hypothesis that UMP- an increase in the monetary base- has a positive and significant influence on income inequality - Gini coefficient. So we have to assume that our hypothesis is true.

14 Future Research

In this paper we have investigated one particular aspect, namely the portfolio channel, as a link between UMP and income inequality. We advise that other channels have to be investigated as well to compare their effects on income inequality. In a couple of years, when more data is available and the effects are better known, we advocate to test our model again.

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Appendix A

Table 1 Lag length Criteria baseline model

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1041.476	NA	9.77e-20	-32.42113	-32.28620	-32.36798
1	1078.387	68.05386*	5.09e-20*	-33.07459*	-32.39994*	-32.80881*
2	1087.003	14.80869	6.45e-20	-32.84384	-31.62947	-32.36544
3	1099.622	20.11217	7.28e-20	-32.73820	-30.98410	-32.04717
4	1109.380	14.33136	9.11e-20	-32.54312	-30.24930	-31.63947
5	1125.076	21.09209	9.65e-20	-32.53363	-29.70010	-31.41736
6	1139.856	18.01248	1.08e-19	-32.49549	-29.12224	-31.16659

Notes:
- 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

Table 2 Remained autocorrelation in CPI , P=2

Date: 05/15/15 Time: 10:02
Sample: 1997Q1 2014Q3
Included observations: 69

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.01...	-0.01...	0.0168	0.897
		2	-0.11...	-0.11...	0.9825	0.612
		3	0.022	0.019	1.0199	0.796
		4	-0.31...	-0.33...	8.4591	0.076
		5	0.047	0.051	8.6298	0.125
		6	0.227	0.161	12.637	0.049
		7	-0.04...	-0.02...	12.796	0.077
		8	-0.00...	-0.07...	12.797	0.119
		9	-0.09...	-0.09...	13.605	0.137
		1...	-0.07...	0.046	14.068	0.170
		1...	0.134	0.095	15.575	0.158
		1...	0.137	0.100	17.188	0.143
		1...	-0.08...	-0.13...	17.876	0.162
		1...	0.208	0.281	21.714	0.085
		1...	-0.05...	0.029	21.943	0.109
		1...	-0.13...	-0.03...	23.593	0.099
		1...	0.091	-0.05...	24.367	0.110
		1...	-0.24...	-0.21...	30.063	0.037
		1...	-0.13...	-0.11...	31.841	0.033
		2...	0.103	-0.05...	32.908	0.035
		2...	-0.16...	-0.19...	35.725	0.023
		2...	0.157	0.049	38.302	0.017
		2...	0.014	-0.08...	38.324	0.024
		2...	-0.12...	-0.00...	39.944	0.022
		2...	-0.05...	-0.20...	40.314	0.027
		2...	-0.01...	-0.04...	40.331	0.036
		2...	-0.08...	-0.12...	41.159	0.040
		2...	0.084	-0.03...	41.995	0.043

Remained autocorrelation in Gini

Date: 05/15/15 Time: 10:16
Sample: 1997Q1 2014Q3
Included observations: 69

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.04...	-0.04...	0.1237	0.725
		2	-0.02...	-0.02...	0.1588	0.924
		3	0.202	0.201	3.1917	0.363
		4	-0.13...	-0.12...	4.4916	0.344
		5	-0.01...	-0.01...	4.4991	0.480
		6	-0.27...	-0.33...	10.333	0.111
		7	0.088	0.153	10.944	0.141
		8	0.078	0.050	11.427	0.179
		9	-0.30...	-0.19...	19.019	0.025
		1...	0.168	0.056	21.373	0.019
		1...	-0.12...	-0.19...	22.722	0.019
		1...	-0.09...	-0.03...	23.527	0.024
		1...	0.094	0.052	24.294	0.029
		1...	-0.10...	-0.01...	25.201	0.033
		1...	0.100	-0.05...	26.105	0.037
		1...	-0.14...	-0.13...	27.972	0.032
		1...	-0.07...	-0.12...	28.439	0.040
		1...	0.084	-0.02...	29.124	0.047
		1...	-0.17...	-0.00...	32.008	0.031
		2...	0.093	-0.01...	32.870	0.035
		2...	0.132	0.118	34.636	0.031
		2...	-0.02...	-0.08...	34.718	0.041
		2...	0.113	0.003	36.085	0.040
		2...	-0.11...	-0.13...	37.517	0.039
		2...	-0.09...	-0.21...	38.557	0.041
		2...	0.039	0.076	38.734	0.052
		2...	-0.21...	-0.18...	43.954	0.021
		2...	-0.01...	-0.13...	43.986	0.028

Table 3 Remained autocorrelation in CPI , P=3

Date: 05/15/15 Time: 11:09
Sample: 1997Q1 2014Q3
Included observations: 68

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.004	0.004	0.0013	0.971
		2	-0.05...	-0.05...	0.2003	0.905
		3	0.016	0.016	0.2187	0.975
		4	-0.31...	-0.32...	7.7392	0.102
		5	0.034	0.046	7.8269	0.166
		6	0.191	0.169	10.630	0.101
		7	-0.09...	-0.09...	11.282	0.127
		8	0.014	-0.08...	11.298	0.185
		9	-0.10...	-0.10...	12.239	0.200
		1...	-0.06...	0.065	12.558	0.249
		1...	0.131	0.071	13.996	0.233
		1...	0.168	0.141	16.391	0.174
		1...	-0.09...	-0.16...	17.222	0.189
		1...	0.237	0.308	22.171	0.075
		1...	-0.04...	0.022	22.367	0.099
		1...	-0.13...	-0.05...	23.998	0.090
		1...	0.066	-0.08...	24.405	0.109
		1...	-0.25...	-0.18...	30.463	0.033
		1...	-0.13...	-0.07...	32.316	0.029
		2...	0.106	-0.02...	33.428	0.030
		2...	-0.16...	-0.14...	36.114	0.021
		2...	0.190	0.086	39.860	0.011
		2...	-0.00...	-0.06...	39.862	0.016
		2...	-0.10...	-0.01...	41.071	0.016
		2...	-0.07...	-0.23...	41.649	0.020
		2...	-0.02...	-0.05...	41.718	0.026
		2...	-0.08...	-0.09...	42.470	0.030
		2...	0.083	-0.04...	43.291	0.033

Table 4: No auto correlation in CPI anymore P=4

,

Date: 05/15/15 Time: 11:12
Sample: 1997Q1 2014Q3
Included observations: 66

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.107	0.107	0.7896	0.374
		2	0.134	0.124	2.0432	0.360
		3	-0.05...	-0.07...	2.2200	0.528
		4	-0.11...	-0.11...	3.1184	0.538
		5	-0.00...	0.034	3.1220	0.681
		6	0.013	0.042	3.1351	0.792
		7	-0.14...	-0.17...	4.6863	0.698
		8	-0.00...	0.010	4.6865	0.791
		9	-0.06...	-0.01...	5.0249	0.832
		1...	0.062	0.061	5.3367	0.868
		1...	0.096	0.061	6.0826	0.868
		1...	0.188	0.167	9.0077	0.702
		1...	-0.05...	-0.11...	9.2512	0.754
		1...	0.167	0.153	11.650	0.634
		1...	-0.00...	0.036	11.650	0.705
		1...	-0.01...	-0.06...	11.670	0.766
		1...	0.028	0.034	11.742	0.815
		1...	-0.17...	-0.13...	14.552	0.692
		1...	-0.13...	-0.07...	16.224	0.642
		2...	0.009	0.044	16.232	0.702
		2...	-0.12...	-0.07...	17.734	0.666
		2...	0.221	0.179	22.714	0.418
		2...	-0.01...	-0.06...	22.738	0.476
		2...	-0.07...	-0.15...	23.296	0.502
		2...	-0.14...	-0.16...	25.508	0.434
		2...	-0.03...	-0.00...	25.674	0.481
		2...	-0.11...	-0.10...	27.235	0.451
		2...	0.014	-0.05...	27.257	0.504

Table 6 VAR of baseline model in levels:

Vector Autoregression Estimates
Date: 07/25/15 Time: 14:10
Sample (adjusted): 1998Q1 2014Q3
Included observations: 67 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	LOG_GDP	LOG_CPI1	LOG_MB	GINI
LOG_GDP(-1)	1.079403			
	(0.15220)			
	[7.09209]			
LOG_CPI1(-1)		1.063392	2.605612	0.206727
		(0.14306)	(2.02182)	(0.12277)
		[7.43326]	[1.28875]	[1.68386]
LOG_CPI1(-2)		-0.301285		0.218642
		(0.20109)		(0.17257)
		[-1.49824]		[1.26696]
LOG_CPI1(-4)	0.202289			
	(0.16220)			
	[1.34717]			
LOG_MB(-1)		-0.041031	1.054467	
		(0.01087)	(0.15368)	
		[-3.77333]	[6.86141]	
LOG_MB(-2)	0.033665	0.046107		0.028289
	(0.02572)	(0.01761)		(0.01511)
	[1.30875]	[2.61856]		[1.87213]
LOG_MB(-4)		0.017333	0.304793	
		(0.01289)	(0.18211)	
		[1.34518]	[1.67367]	
GINI(-1)				0.177494
				(0.13798)
				[1.28641]
GINI(-2)		-0.249721	-4.694505	0.292056
		(0.15185)	(2.14603)	(0.13031)
		[-1.64455]	[-2.18753]	[2.24121]
GINI(-3)				0.237030
				(0.13574)
				[1.74615]
GINI(-4)		0.226729		-0.153475
		(0.14795)		(0.12696)
		[1.53250]		[-1.20880]
C				0.169297
				(0.05600)
				[3.02341]

R-squared	0.899267	0.899074	0.893755	0.839676
Adj. R-squared	0.899033	0.898778	0.891756	0.839446
Sum sq. resids	0.000347	0.000163	0.032514	0.000120
S.E. equation	0.002636	0.001804	0.025501	0.001548
F-statistic	4264.768	3373.520	497.2755	48.67908
Log likelihood	312.6155	338.0111	160.5617	348.2584
Akaike AIC	-8.824342	-9.582420	-4.285423	-9.888310
Schwarz SC	-8.264942	-9.023020	-3.726024	-9.328910
Mean dependent	4.113191	2.295380	3.046041	0.467766
S.D. dependent	0.084788	0.051624	0.280867	0.005487

Determinant resid covariance (dof adj.)	2.43E-20
Determinant resid covariance	7.53E-21
Log likelihood	1171.965
Akaike information criterion	-32.95418
Schwarz criterion	-30.71658

Table 7 : Impulse response functions

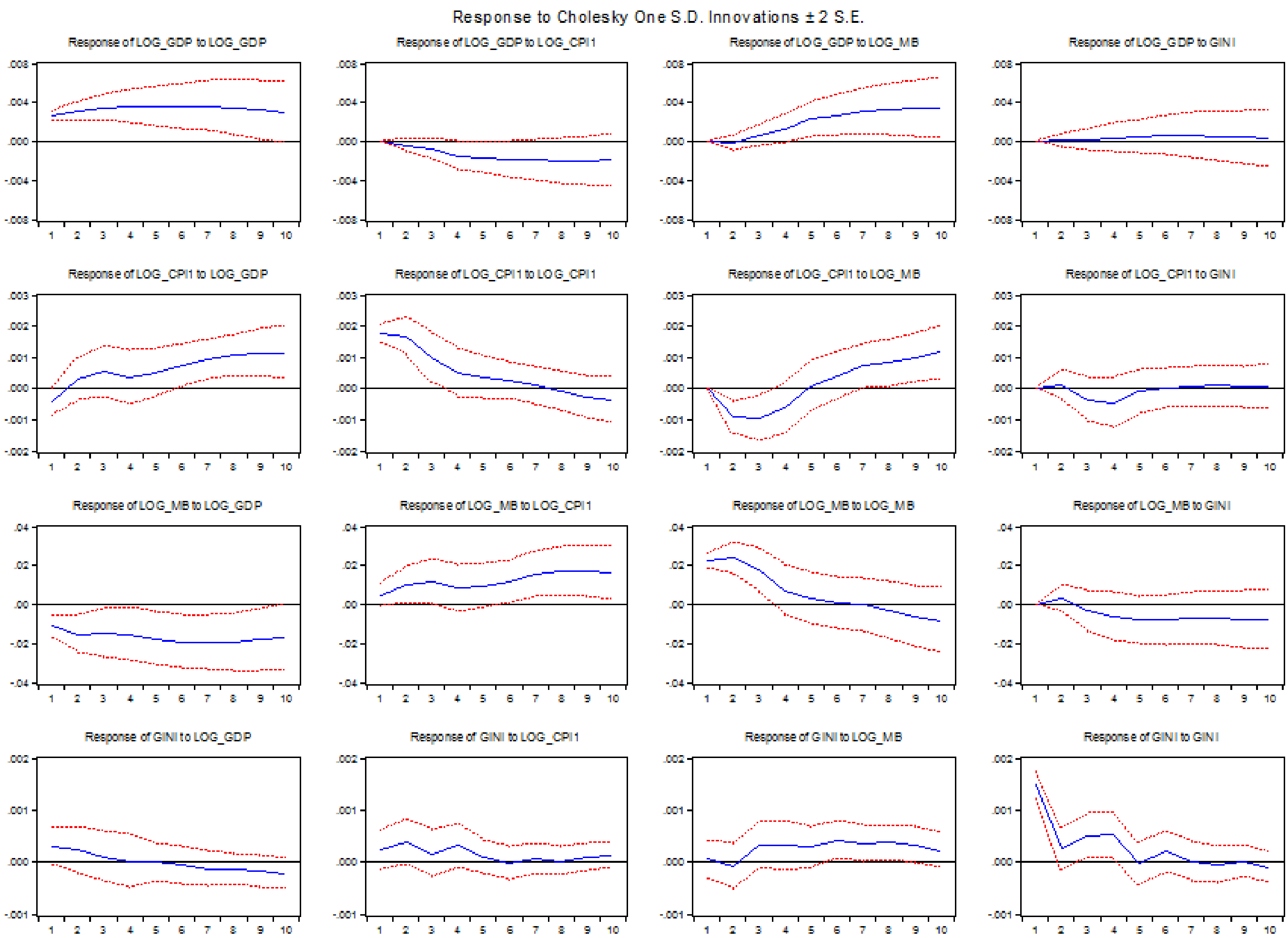

Table 8 Lag length criteria

Lag	LogL	LR	FPE	AIC	SC	HQ
0	781.4793	NA	2.89e-17	-23.89167	-23.72441	-23.82567
1	1244.178	839.9753	4.11e-23	-37.35931	-36.35574*	-36.96334*
2	1273.711	49.07169	3.62e-23*	-37.49881	-35.65895	-36.77287
3	1294.242	30.95339	4.31e-23	-37.36128	-34.68511	-36.30536
4	1320.676	35.78855	4.41e-23	-37.40543	-33.89296	-36.01953
5	1341.261	24.70133	5.68e-23	-37.26957	-32.92079	-35.55370
6	1377.319	37.72205*	4.86e-23	-37.60981*	-32.42473	-35.56396

Table 10: Choosing the appropriate model

Data Trend:	None	None	Linear	Linear	Quadratic
Rank or No. of CEs	No Intercept No Trend	Intercept No Trend	Intercept No Trend	Intercept Trend	Intercept Trend
	Log Likelihood by Rank (rows) and Model (columns)				
0	1294.215	1294.215	1307.021	1307.021	1314.027
1	1314.025	1322.503	1334.890	1336.195	1341.562
2	1329.403	1338.601	1344.789	1349.901	1353.804
3	1336.391	1345.977	1352.070	1359.776	1363.578
4	1341.342	1352.626	1357.247	1365.784	1369.511
5	1341.343	1357.371	1357.371	1370.089	1370.089
	Akaike Information Criteria by Rank (rows) and Model (columns)				
0	-36.18833	-36.18833	-36.42489	-36.42489	-36.48567
1	-36.48560	-36.71222	-36.96635	-36.97561	-37.01702
2	-36.64858	-36.86669	-36.96331	-37.05761	-37.08498*
3	-36.55729	-36.75688	-36.88090	-37.02352	-37.07813
4	-36.40432	-36.62503	-36.73475	-36.87224	-36.95487
5	-36.10131	-36.43548	-36.43548	-36.66935	-36.66935
	Schwarz Criteria by Rank (rows) and Model (columns)				
0	-32.87067	-32.87067	-32.94135	-32.94135	-32.83625
1	-32.83618	-33.02962	-33.15104*	-33.12712	-33.03583
2	-32.66739	-32.81915	-32.81624	-32.84419	-32.77203
3	-32.24433	-32.34439	-32.40206	-32.44516	-32.43341
4	-31.75959	-31.84760	-31.92415	-31.92893	-31.97839
5	-31.12482	-31.29311	-31.29311	-31.36110	-31.36110

Table 11

Vector Error Correction Estimates
Date: 08/16/15 Time: 11:16
Sample (adjusted): 1998Q1 2014Q3
Included observations: 67 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
LOG_GDP(-1)	1.000000
LOG_CPI1(-1)	-2.249834
	(0.04599)
	[-48.9250]
LOG_MB(-1)	0.099253
	(0.00934)
	[10.6260]
LOG_S(-1)	-0.078211
	(0.01317)
	[-5.93948]
GINI(-1)	0.753699
	(0.55949)
	[1.34711]
C	0.638105

Error Correction:	D(LOG_GDP)	D(LOG_CPI1)	D(LOG_MB)	D(LOG_S)	D(GINI)
CointEq1	0.325937		-2.299161	1.303581	0.076347
	(0.05186)		(0.58429)	(0.82847)	(0.03907)
	[6.28532]		[-3.93497]	[1.57349]	[1.95423]
D(LOG_GDP(-1))	-0.674817		3.413460		-0.164931
	(0.17795)		(2.00499)		(0.13406)
	[-3.79225]		[1.70249]		[-1.23027]
D(LOG_GDP(-2))	-0.321444		3.016402		
	(0.15963)		(1.79858)		
	[-2.01371]		[1.67710]		
D(LOG_GDP(-3))	-0.204811				-0.154666
	(0.14303)				(0.10776)
	[-1.43191]				[-1.43531]
D(LOG_CPI1(-1))	0.481733	0.272042			0.402336
	(0.17984)	(0.16426)			(0.13549)
	[2.67871]	[1.65615]			[2.96958]
D(LOG_CPI1(-2))	0.516490		-4.342768		0.184155
	(0.18462)		(2.08015)		(0.13909)
	[2.79762]		[-2.08772]		[1.32403]
D(LOG_CPI1(-3))	0.222657		-3.839717		0.165763
	(0.14613)		(1.64647)		(0.11009)
	[1.52372]		[-2.33208]		[1.50572]

D(LOG_MB(-1))	-0.040206	-0.049298	0.313442		
	(0.01266)	(0.01157)	(0.14270)		
	[-3.17471]	[-4.26173]	[2.19657]		
D(LOG_MB(-2))					0.019577
					(0.01129)
					[1.73346]
D(LOG_MB(-3))			-0.319893		0.005276
			(0.16367)		(0.01094)
			[-1.95455]		[1.48213]
D(LOG_S(-1))	0.041400		-0.187307		0.024246
	(0.01064)		(0.11991)		(0.00802)
	[3.89015]		[-1.56208]		[3.02418]
D(LOG_S(-2))	0.042141	0.013555	-0.160030		
	(0.01111)	(0.01015)	(0.12518)		
	[3.79297]	[1.33569]	[-1.27836]		
D(LOG_S(-3))	0.036578		-0.278602		0.010303
	(0.01071)		(0.12066)		(0.00807)
	[3.41564]		[-2.30897]		[1.27708]
D(GINI(-1))	-0.372790		5.261844		-0.751393
	(0.18498)		(2.08422)		(0.13936)
	[-2.01531]		[2.52461]		[-5.39180]
D(GINI(-2))	-0.436635				-0.330018
	(0.20817)				(0.15683)
	[-2.09751]				[-2.10432]
D(GINI(-3))	-0.313751	-0.331345			0.066439
	(0.16866)	(0.15405)			(0.12706)
	[-1.86031]	[-2.15093]			[0.52289]
C	0.007064	0.002883	0.008229	0.026406	0.000187
	(0.00132)	(0.00121)	(0.01489)	(0.02111)	(0.00100)
	[5.34550]	[2.38828]	[0.55266]	[1.25079]	[0.18764]

R-squared	0.676850	0.508456	0.498156	0.304431	0.518611
Adj. R-squared	0.573442	0.351162	0.337566	0.081849	0.364566
Sum sq. resids	0.000215	0.000180	0.027324	0.054933	0.000122
S.E. equation	0.002075	0.001895	0.023377	0.033146	0.001563
F-statistic	6.545427	3.232520	3.102032	1.367724	3.366630
Log likelihood	328.6564	334.7264	166.3885	142.9935	347.6302
Akaike AIC	-9.303176	-9.484371	-4.459357	-3.761000	-9.869557
Schwarz SC	-8.743776	-8.924971	-3.899957	-3.201601	-9.310158
Mean dependent	0.004502	0.002510	0.013514	0.004663	0.000239
S.D. dependent	0.003177	0.002353	0.028722	0.034592	0.001961

Determinant resid covariance (dof adj.)	1.35E-23
Determinant resid covariance	3.13E-24
Log likelihood	1337.725
Akaike information criterion	-37.24554
Schwarz criterion	-34.28401

Table 12

Dependent Variable: LOG_GDP
Method: Least Squares
Date: 07/30/15 Time: 13:37
Sample: 1997Q1 2014Q3
Included observations: 71

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG_CPI1	1.979909	0.051224	38.65182	0.0000
LOG_MB	-0.071875	0.010759	-6.680187	0.0000
LOG_S	0.076587	0.014548	5.264478	0.0000
GINI	-0.173816	0.567115	-0.306492	0.7602
C	-0.368806	0.202434	-1.821860	0.0730

R-squared	0.992128	Mean dependent var	4.103144
Adjusted R-squared	0.991651	S.D. dependent var	0.092174
S.E. of regression	0.008422	Akaike info criterion	-6.648119
Sum squared resid	0.004681	Schwarz criterion	-6.488775
Log likelihood	241.0082	Hannan-Quinn criter.	-6.584753
F-statistic	2079.662	Durbin-Watson stat	0.351362
Prob(F-statistic)	0.000000		

Table 13

Null Hypothesis: RESIDUALSGDP has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.845757	0.0050
Test critical values:	1% level	-2.598416	
	5% level	-1.945525	
	10% level	-1.613760	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RESIDUALSGDP)
Method: Least Squares
Date: 07/30/15 Time: 14:02
Sample (adjusted): 1997Q2 2014Q3
Included observations: 70 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RESIDUALSGDP(-1)	-0.191608	0.067331	-2.845757	0.0058

R-squared	0.102953	Mean dependent var	0.000233
Adjusted R-squared	0.102953	S.D. dependent var	0.004862
S.E. of regression	0.004605	Akaike info criterion	-7.909312
Sum squared resid	0.001463	Schwarz criterion	-7.877191

Log likelihood	277.8259	Hannan-Quinn criter.	-7.896553
Durbin-Watson stat	1.741968		

Table 14

Dependent Variable: D(LOG_GDP)
Method: Least Squares
Date: 08/01/15 Time: 13:19
Sample (adjusted): 1997Q3 2014Q3
Included observations: 69 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RESIDUGINI(-1)	0.243453	0.041834	3.429124	0.0011
D(LOG_CPILAG)	0.343265	0.141459	1.012771	0.3150
D(LOG_MBLAG)	-0.021639	0.012786	-1.692355	0.0955
D(LOG_SLAG)	0.025015	0.010197	2.453287	0.0169
D(GINI(-1))	-0.024426	0.163998	-0.148941	0.8821
C	0.004322	0.000531	8.134534	0.0000

R-squared	0.348571	Mean dependent var	0.004543
Adjusted R-squared	0.296870	S.D. dependent var	0.003145
S.E. of regression	0.002637	Akaike info criterion	-8.955451
Sum squared resid	0.000438	Schwarz criterion	-8.761181
Log likelihood	314.9631	Hannan-Quinn criter.	-8.878377
F-statistic	6.742081	Durbin-Watson stat	2.047598
Prob(F-statistic)	0.000043		

Table 15:

Vector Error Correction Estimates
Date: 06/18/15 Time: 15:11
Sample (adjusted): 1998Q2 2014Q3
Included observations: 66 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegration Restrictions:
B(1,2)=0, B(1,3)=0, B(1,4)=0, B(1,5)=0
Convergence achieved after 1 iterations.
Not all cointegrating vectors are identified
LR test for binding restrictions (rank = 1):

Chi-square(4)	40.29310
Probability	0.000000

Cointegrating Eq:	CointEq1
LGDP(-1)	-4.500489
LCPI(-1)	0.000000
LMB(-1)	0.000000

LSP500(-1)	0.000000				
GINI(-1)	0.000000				
C	18.50235				

Error Correction:	D(LGDP)	D(LCPI)	D(LMB)	D(LSP500)	D(GINI)
CointEq1	0.001772	-0.001381	-0.007461	-0.015301	-0.000631
	(0.00112)	(0.00075)	(0.01141)	(0.01429)	(0.00068)
	[1.57980]	[-1.83182]	[-0.65398]	[-1.07084]	[-0.92846]
D(LGDP(-1))	0.030926	0.101123	-1.818238	2.027726	0.066444
	(0.18016)	(0.12110)	(1.83249)	(2.29521)	(0.10918)
	[0.17166]	[0.83503]	[-0.99222]	[0.88346]	[0.60860]
D(LGDP(-2))	0.204403	0.000427	-0.890878	2.168864	0.085223
	(0.18113)	(0.12175)	(1.84234)	(2.30755)	(0.10976)
	[1.12852]	[0.00351]	[-0.48356]	[0.93990]	[0.77643]
D(LGDP(-3))	0.152568	0.075532	-2.032174	2.233084	-0.004534
	(0.18198)	(0.12233)	(1.85106)	(2.31847)	(0.11028)
	[0.83836]	[0.61746]	[-1.09784]	[0.96317]	[-0.04111]
D(LGDP(-4))	0.255169	0.139066	-0.877453	2.030438	0.079992
	(0.17244)	(0.11592)	(1.75404)	(2.19696)	(0.10450)
	[1.47972]	[1.19971]	[-0.50025]	[0.92420]	[0.76546]
D(LCPI(-1))	0.020122	0.122316	0.598867	-3.630463	0.254896
	(0.21388)	(0.14377)	(2.17553)	(2.72488)	(0.12961)
	[0.09408]	[0.85077]	[0.27527]	[-1.33234]	[1.96659]
D(LCPI(-2))	-0.031852	-0.169884	-0.215485	-3.155576	0.066359
	(0.21901)	(0.14722)	(2.22771)	(2.79024)	(0.13272)
	[-0.14543]	[-1.15395]	[-0.09673]	[-1.13093]	[0.49999]
D(LCPI(-3))	-0.250975	-0.004371	0.339243	-4.134952	0.071005
	(0.21954)	(0.14757)	(2.23307)	(2.79695)	(0.13304)
	[-1.14319]	[-0.02962]	[0.15192]	[-1.47838]	[0.53370]
D(LCPI(-4))	-0.060094	-0.323449	0.901839	0.253720	-0.103107
	(0.17828)	(0.11984)	(1.81339)	(2.27130)	(0.10804)
	[-0.33708]	[-2.69903]	[0.49732]	[0.11171]	[-0.95437]
D(LMB(-1))	-0.017947	-0.053118	0.194079	0.051039	0.000883
	(0.01684)	(0.01132)	(0.17130)	(0.21455)	(0.01021)
	[-1.06572]	[-4.69234]	[1.13300]	[0.23789]	[0.08654]
D(LMB(-2))	0.035450	0.005829	-0.198470	0.284350	0.031076
	(0.01944)	(0.01307)	(0.19771)	(0.24764)	(0.01178)
	[1.82377]	[0.44611]	[-1.00384]	[1.14826]	[2.63824]
D(LMB(-3))	0.012085	-0.005621	-0.341560	0.148393	0.008440
	(0.01959)	(0.01317)	(0.19931)	(0.24964)	(0.01187)
	[0.61672]	[-0.42678]	[-1.71369]	[0.59443]	[0.71074]
D(LMB(-4))	0.006259	0.004100	0.086882	0.149495	0.006049

	(0.01965)	(0.01321)	(0.19986)	(0.25033)	(0.01191)
	[0.31854]	[0.31044]	[0.43471]	[0.59719]	[0.50804]
D(LSP500(-1))	0.018213	-0.011955	-0.006457	-0.040717	0.014819
	(0.01331)	(0.00895)	(0.13541)	(0.16961)	(0.00807)
	[1.36809]	[-1.33596]	[-0.04768]	[-0.24007]	[1.83693]
D(LSP500(-2))	0.019448	0.002138	0.028679	-0.084353	-0.005071
	(0.01410)	(0.00948)	(0.14341)	(0.17963)	(0.00854)
	[1.37938]	[0.22561]	[0.19997]	[-0.46960]	[-0.59353]
D(LSP500(-3))	0.011637	-0.010957	-0.027889	-0.031772	-0.000722
	(0.01425)	(0.00958)	(0.14493)	(0.18153)	(0.00863)
	[0.81674]	[-1.14397]	[-0.19243]	[-0.17502]	[-0.08359]
D(LSP500(-4))	-0.015178	-0.005139	0.069822	-0.105393	-0.015139
	(0.01308)	(0.00879)	(0.13301)	(0.16660)	(0.00792)
	[-1.16064]	[-0.58466]	[0.52492]	[-0.63261]	[-1.91038]
D(GINI(-1))	-0.042278	0.112512	3.378262	-1.683264	-0.704734
	(0.24380)	(0.16388)	(2.47982)	(3.10601)	(0.14774)
	[-0.17342]	[0.68655]	[1.36230]	[-0.54194]	[-4.77003]
D(GINI(-2))	-0.002631	-0.161367	-2.010217	-0.408392	-0.293312
	(0.28725)	(0.19309)	(2.92183)	(3.65963)	(0.17408)
	[-0.00916]	[-0.83571]	[-0.68800]	[-0.11159]	[-1.68497]
D(GINI(-3))	0.173993	-0.459392	-3.335309	2.135781	0.112572
	(0.26638)	(0.17906)	(2.70954)	(3.39374)	(0.16143)
	[0.65317]	[-2.56556]	[-1.23095]	[0.62933]	[0.69735]
D(GINI(-4))	0.409468	-0.286732	-4.130196	4.576480	0.039650
	(0.23039)	(0.15487)	(2.34348)	(2.93524)	(0.13962)
	[1.77725]	[-1.85144]	[-1.76242]	[1.55915]	[0.28399]
C	0.001637	0.002995	0.039624	-0.015780	-0.001889
	(0.00184)	(0.00123)	(0.01868)	(0.02340)	(0.00111)
	[0.89127]	[2.42598]	[2.12118]	[-0.67445]	[-1.69734]
R-squared	0.530274	0.613124	0.405222	0.340750	0.547403
Adj. R-squared	0.306087	0.428478	0.121350	0.026107	0.331391
Sum sq. resids	0.000313	0.000141	0.032356	0.050760	0.000115
S.E. equation	0.002666	0.001792	0.027118	0.033965	0.001616
F-statistic	2.365320	3.320546	1.427484	1.082975	2.534131
Log likelihood	310.9234	337.1390	157.8298	142.9698	343.9811
Akaike AIC	-8.755255	-9.549665	-4.116053	-3.665751	-9.757005
Schwarz SC	-8.025370	-8.819781	-3.386168	-2.935866	-9.027120
Mean dependent	0.004494	0.002513	0.013616	0.003994	0.000238
S.D. dependent	0.003200	0.002371	0.028930	0.034418	0.001976

Determinant resid covariance (dof adj.)	2.60E-23
Determinant resid covariance	3.43E-24
Log likelihood	1314.743
Akaike information criterion	-36.35585
Schwarz criterion	-32.54054

Table 16

Vector Error Correction Estimates
Date: 06/18/15 Time: 15:49
Sample (adjusted): 1998Q2 2014Q3
Included observations: 66 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegration Restrictions:	
A(2,1)=0, A(3,1)=0, A(4,1)=0, A(5,1)=0	
Convergence achieved after 8 iterations.	
Not all cointegrating vectors are identified	
LR test for binding restrictions (rank = 1):	
Chi-square(4)	24.60457
Probability	0.000060

Cointegrating Eq:	CointEq1
LGDP(-1)	264.3479
LCPI(-1)	-604.5586
LMB(-1)	27.84631
LSP500(-1)	-22.38033
GINI(-1)	168.6918
C	205.8867

Error Correction:	D(LGDP)	D(LCPI)	D(LMB)	D(LSP500)	D(GINI)
CointEq1	0.001340	0.000000	0.000000	0.000000	0.000000
	(0.00022)	(0.00000)	(0.00000)	(0.00000)	(0.00000)
	[6.13275]	[NA]	[NA]	[NA]	[NA]
D(LGDP(-1))	-0.884349	0.211775	4.794645	-2.366395	-0.113319
	(0.19905)	(0.18591)	(2.41224)	(3.42076)	(0.16314)
	[-4.44280]	[1.13915]	[1.98763]	[-0.69177]	[-0.69462]
D(LGDP(-2))	-0.658822	0.095289	5.389410	-2.169141	-0.092286
	(0.19367)	(0.18088)	(2.34701)	(3.32827)	(0.15873)
	[-3.40178]	[0.52681]	[2.29629]	[-0.65173]	[-0.58141]
D(LGDP(-3))	-0.492142	0.160980	2.591509	-0.708939	-0.124859
	(0.16941)	(0.15822)	(2.05301)	(2.91135)	(0.13884)
	[-2.90504]	[1.01743]	[1.26230]	[-0.24351]	[-0.89928]
D(LGDP(-4))	-0.127423	0.178348	1.918694	0.051412	-0.001000
	(0.14123)	(0.13190)	(1.71149)	(2.42704)	(0.11575)
	[-0.90225]	[1.35213]	[1.12107]	[0.02118]	[-0.00864]
D(LCPI(-1))	0.775747	0.027048	-4.842606	-0.082743	0.400016
	(0.19919)	(0.18604)	(2.41393)	(3.42317)	(0.16325)
	[3.89447]	[0.14539]	[-2.00611]	[-0.02417]	[2.45029]

D(LCPI(-2))	0.819281	-0.289216	-6.289716	0.595276	0.219735
	(0.21104)	(0.19711)	(2.55755)	(3.62683)	(0.17297)
	[3.88206]	[-1.46731]	[-2.45927]	[0.16413]	[1.27040]
D(LCPI(-3))	0.498903	-0.081200	-5.141938	-0.252743	0.229885
	(0.20245)	(0.18908)	(2.45339)	(3.47913)	(0.16592)
	[2.46435]	[-0.42945]	[-2.09585]	[-0.07265]	[1.38551]
D(LCPI(-4))	0.497936	-0.390415	-3.132210	2.942873	0.006908
	(0.15930)	(0.14878)	(1.93045)	(2.73754)	(0.13055)
	[3.12586]	[-2.62418]	[-1.62253]	[1.07501]	[0.05291]
D(LMB(-1))	-0.037845	-0.049819	0.333752	-0.026253	-0.002275
	(0.01275)	(0.01191)	(0.15456)	(0.21918)	(0.01045)
	[-2.96735]	[-4.18235]	[2.15936]	[-0.11978]	[-0.21764]
D(LMB(-2))	-0.016817	0.014884	0.166631	0.089266	0.023107
	(0.01639)	(0.01531)	(0.19867)	(0.28174)	(0.01344)
	[-1.02581]	[0.97211]	[0.83872]	[0.31684]	[1.71978]
D(LMB(-3))	-0.002611	-0.002830	-0.240029	0.098541	0.006405
	(0.01456)	(0.01360)	(0.17646)	(0.25023)	(0.01193)
	[-0.17930]	[-0.20813]	[-1.36028]	[0.39380]	[0.53670]
D(LMB(-4))	0.010458	0.005667	0.047047	0.211983	0.008615
	(0.01438)	(0.01343)	(0.17425)	(0.24710)	(0.01178)
	[0.72734]	[0.42201]	[0.27000]	[0.85788]	[0.73103]
D(LSP500(-1))	0.060943	-0.015730	-0.321545	0.192805	0.024379
	(0.01201)	(0.01121)	(0.14551)	(0.20634)	(0.00984)
	[5.07562]	[-1.40270]	[-2.20982]	[0.93440]	[2.47738]
D(LSP500(-2))	0.066064	-0.001733	-0.316196	0.175449	0.005565
	(0.01284)	(0.01199)	(0.15560)	(0.22066)	(0.01052)
	[5.14510]	[-0.14447]	[-2.03204]	[0.79511]	[0.52881]
D(LSP500(-3))	0.057499	-0.015282	-0.364818	0.213271	0.009308
	(0.01287)	(0.01202)	(0.15593)	(0.22112)	(0.01055)
	[4.46870]	[-1.27170]	[-2.33962]	[0.96449]	[0.88267]
D(LSP500(-4))	0.026271	-0.008932	-0.235219	0.118445	-0.005977
	(0.01175)	(0.01097)	(0.14236)	(0.20188)	(0.00963)
	[2.23636]	[-0.81416]	[-1.65229]	[0.58671]	[-0.62078]
D(GINI(-1))	-0.595761	0.205257	7.258945	-3.813400	-0.791765
	(0.19870)	(0.18558)	(2.40794)	(3.41467)	(0.16285)
	[-2.99833]	[1.10606]	[3.01459]	[-1.11677]	[-4.86200]
D(GINI(-2))	-0.709506	-0.042247	2.942885	-3.115162	-0.403899
	(0.23785)	(0.22214)	(2.88244)	(4.08755)	(0.19494)
	[-2.98297]	[-0.19018]	[1.02097]	[-0.76211]	[-2.07194]
D(GINI(-3))	-0.449227	-0.345445	0.990767	-0.068567	0.022560
	(0.21728)	(0.20293)	(2.63308)	(3.73394)	(0.17807)
	[-2.06755]	[-1.70232]	[0.37628]	[-0.01836]	[0.12669]
D(GINI(-4))	0.053039	-0.208644	-1.715187	3.579402	-0.000988

	(0.17626)	(0.16462)	(2.13606)	(3.02912)	(0.14446)
	[0.30091]	[-1.26741]	[-0.80297]	[1.18167]	[-0.00684]
C	0.007791	0.002159	-0.004415	0.011880	-0.000758
	(0.00167)	(0.00156)	(0.02029)	(0.02877)	(0.00137)
	[4.65422]	[1.38074]	[-0.21763]	[0.41297]	[-0.55243]
R-squared	0.746524	0.596977	0.544409	0.352690	0.553280
Adj. R-squared	0.625547	0.404625	0.326968	0.043746	0.340072
Sum sq. resids	0.000169	0.000147	0.024785	0.049841	0.000113
S.E. equation	0.001958	0.001829	0.023734	0.033656	0.001605
F-statistic	6.170784	3.103564	2.503709	1.141599	2.595031
Log likelihood	331.2804	335.7896	166.6273	143.5729	344.4124
Akaike AIC	-9.372134	-9.508776	-4.382647	-3.684028	-9.770074
Schwarz SC	-8.642249	-8.778891	-3.652762	-2.954144	-9.040189
Mean dependent	0.004494	0.002513	0.013616	0.003994	0.000238
S.D. dependent	0.003200	0.002371	0.028930	0.034418	0.001976

Determinant resid covariance (dof adj.)	1.45E-23
Determinant resid covariance	1.91E-24
Log likelihood	1322.587
Akaike information criterion	-36.59355
Schwarz criterion	-32.77825

Table 18

Vector Error Correction Estimates
Date: 05/30/15 Time: 11:04
Sample (adjusted): 1998Q1 2014Q3
Included observations: 67 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1
LOG_GDP(-1)	1.000000
LOG_CPI1(-1)	-2.249834 (0.04599) [-48.9250]
LOG_MB(-1)	0.099253 (0.00934) [10.6260]
LOG_S(-1)	-0.078211 (0.01317) [-5.93948]
GINI(-1)	0.753699 (0.55949) [1.34711]
C	0.638105

Error Correction:	D(LOG_GDP)	D(LOG_CPI1)	D(LOG_MB)	D(LOG_S)	D(GINI)
CointEq1	0.325937 (0.05186) [6.28532]	0.015004 (0.04737) [0.31677]	-2.299161 (0.58429) [-3.93497]	1.303581 (0.82847) [1.57349]	0.076347 (0.03907) [1.95423]
D(LOG_GDP(-1))	-0.674817 (0.17795) [-3.79225]				
D(LOG_GDP(-2))	-0.321444 (0.15963) [-2.01371]				
D(LOG_GDP(-3))	-0.204811 (0.14303) [-1.43191]				-0.154666 (0.10776) [-1.43531]
D(LOG_CPI1(-1))	0.481733 (0.17984) [2.67871]	0.272042 (0.16426) [1.65615]			0.402336 (0.13549) [2.96958]
D(LOG_CPI1(-2))	0.516490 (0.18462) [2.79762]		-4.342768 (2.08015) [-2.08772]		0.184155 (0.13909) [1.32403]
D(LOG_CPI1(-3))	0.222657		-3.839717		0.165763

	(0.14613)		(1.64647)		(0.11009)
	[1.52372]		[-2.33208]		[1.50572]
D(LOG_MB(-1))	-0.040206	-0.049298	0.313442		
	(0.01266)	(0.01157)	(0.14270)		
	[-3.17471]	[-4.26173]	[2.19657]		
D(LOG_MB(-2))					0.019577
					(0.01129)
					[1.73346]
D(LOG_MB(-3))			-0.319893		
			(0.16367)		
			[-1.95455]		
D(LOG_S(-1))	0.041400		-0.187307		0.024246
	(0.01064)		(0.11991)		(0.00802)
	[3.89015]		[-1.56208]		[3.02418]
D(LOG_S(-2))	0.042141	0.013555	-0.160030		
	(0.01111)	(0.01015)	(0.12518)		
	[3.79297]	[1.33569]	[-1.27836]		
D(LOG_S(-3))	0.036578	-0.004258	-0.278602		0.010303
	(0.01071)	(0.00978)	(0.12066)		(0.00807)
	[3.41564]	[-0.43536]	[-2.30897]		[1.27708]
D(GINI(-1))	-0.372790		5.261844		-0.751393
	(0.18498)		(2.08422)		(0.13936)
	[-2.01531]		[2.52461]		[-5.39180]
D(GINI(-2))	-0.436635				-0.330018
	(0.20817)				(0.15683)
	[-2.09751]				[-2.10432]
D(GINI(-3))	-0.313751	-0.331345			
	(0.16866)	(0.15405)			
	[-1.86031]	[-2.15093]			
C	0.007064	0.002883		0.026406	
	(0.00132)	(0.00121)		(0.02111)	
	[5.34550]	[2.38828]		[1.25079]	
R-squared	0.676850	0.508456	0.498156	0.304431	0.518611
Adj. R-squared	0.573442	0.351162	0.337566	0.081849	0.364566
Sum sq. resids	0.000215	0.000180	0.027324	0.054933	0.000122
S.E. equation	0.002075	0.001895	0.023377	0.033146	0.001563
F-statistic	6.545427	3.232520	3.102032	1.367724	3.366630
Log likelihood	328.6564	334.7264	166.3885	142.9935	347.6302
Akaike AIC	-9.303176	-9.484371	-4.459357	-3.761000	-9.869557
Schwarz SC	-8.743776	-8.924971	-3.899957	-3.201601	-9.310158
Mean dependent	0.004502	0.002510	0.013514	0.004663	0.000239
S.D. dependent	0.003177	0.002353	0.028722	0.034592	0.001961

Determinant resid covariance (dof adj.)	1.35E-23
Determinant resid covariance	3.13E-24
Log likelihood	1337.725

Akaike information criterion	-37.24554
Schwarz criterion	-34.28401

Table 19:

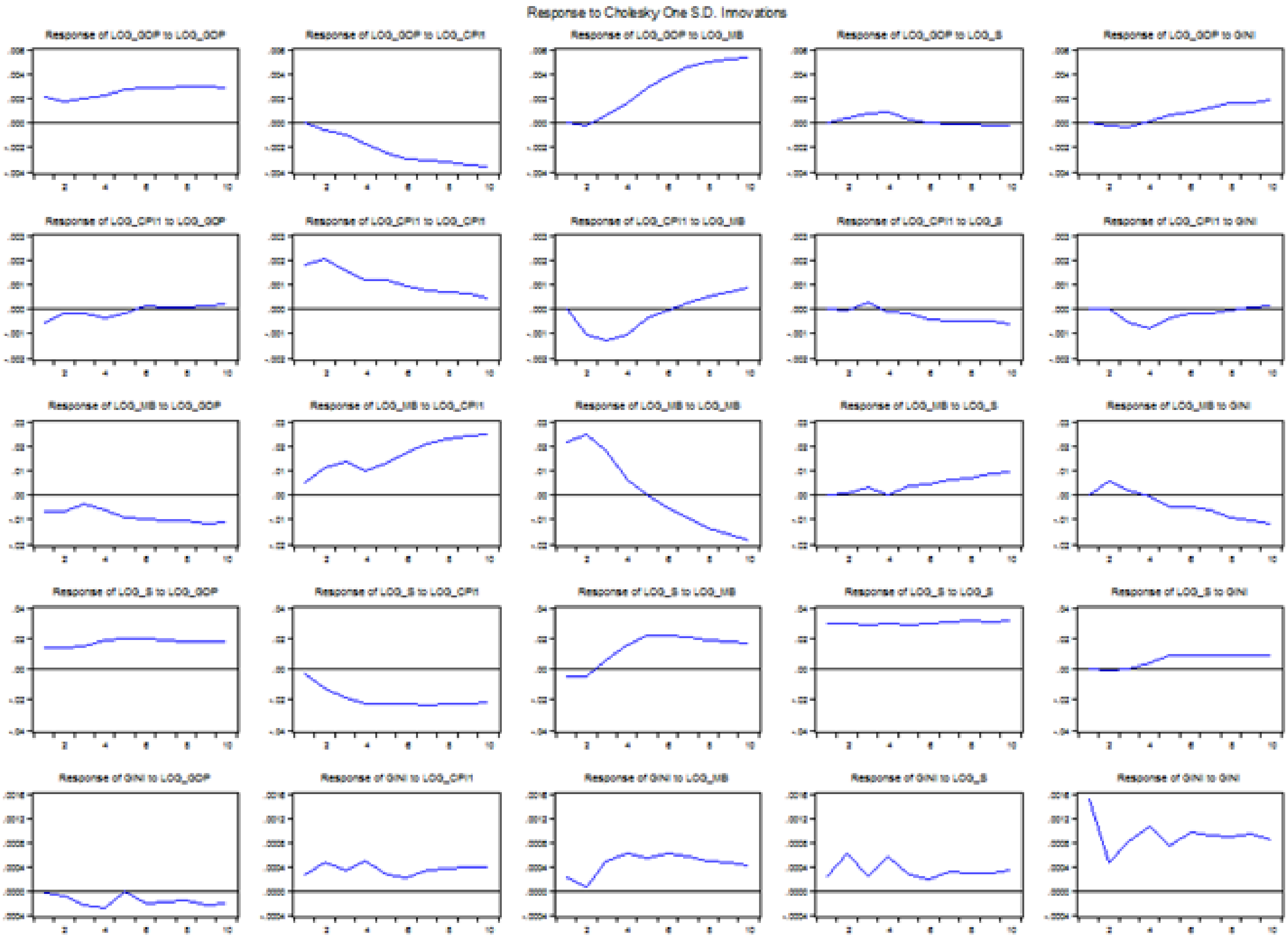

Table 20 A

Period	S.E.	LOG_GDP	LOG_CPI1	LOG_MB	GINI
		Variance Decomposition of GINI:			
1	0.001548	3.955561	2.297291	0.119651	93.62750
2	0.001635	5.438933	7.578826	0.377410	86.60483
3	0.001754	5.035775	7.449837	3.930649	83.58374
4	0.001886	4.363792	9.299567	6.248491	80.08815
5	0.001910	4.252655	9.258202	8.413152	78.07599
6	0.001968	4.092923	8.743666	12.53751	74.62590
7	0.002004	4.348746	8.520870	15.14814	71.98225
8	0.002043	4.633725	8.206519	17.84266	69.31709
9	0.002078	5.233693	8.124043	19.63160	67.01067
10	0.002109	6.140206	8.303266	20.15809	65.39844
11	0.002136	7.259508	8.546210	20.27145	63.92283
12	0.002168	8.654912	9.150614	19.85455	62.33993
13	0.002204	10.09757	9.857474	19.24258	60.80238
14	0.002240	11.49241	10.75870	18.62023	59.12865
15	0.002280	12.72039	11.77848	18.03345	57.46768
16	0.002317	13.72503	12.73557	17.58349	55.95591

Cholesky Ordering: LOG_GDP LOG_CPI1 LOG_MB GINI

Table 20 B

Period	S.E.	LOG_GDP	LOG_CPI1	LOG_MB	LOG_S	GINI
			Variance Decomposition of GINI:			
1	0.001563	0.050312	2.872490	1.689139	2.340827	93.04723
2	0.001804	0.252085	8.773687	1.359723	13.25256	76.36194
3	0.002091	1.402238	9.323282	6.630029	11.08252	71.56193
4	0.002556	2.105738	9.767017	10.23783	12.44731	65.44210
5	0.002739	1.835641	9.423157	12.91705	11.81388	64.01027
6	0.002993	2.083559	8.356226	15.17149	10.32948	64.05925
7	0.003216	2.138878	8.303663	16.26362	9.909776	63.38407
8	0.003408	2.163444	8.473516	16.58493	9.545382	63.23273
9	0.003604	2.328292	8.664393	16.41258	9.208777	63.38595
10	0.003762	2.463209	9.045283	16.27422	9.217026	63.00026
11	0.003924	2.605803	9.342061	16.11631	9.079250	62.85658
12	0.004081	2.714994	9.682335	15.87163	9.039896	62.69115
13	0.004218	2.788733	9.979844	15.68121	9.005901	62.54431
14	0.004358	2.890061	10.23101	15.47528	8.968834	62.43482
15	0.004491	2.961148	10.49981	15.27178	8.983433	62.28383
16	0.004619	3.020209	10.71934	15.09368	8.979305	62.18746

Cholesky Ordering: LOG_GDP LOG_CPI1 LOG_MB LOG_S GINI

Table 21

Dependent Variable: GINI
Method: Least Squares
Date: 08/16/15 Time: 13:22
Sample: 1997Q1 2014Q3
Included observations: 71

Variable	Coefficient	Std. Error	t-Statistic	Prob.
LOG_GDP	-0.008177	0.026679	-0.306492	0.7602
LOG_CPI1	0.050780	0.053651	0.946473	0.3474
LOG_MB	0.009808	0.002770	3.541459	0.0007
LOG_S	0.011549	0.003481	3.317850	0.0015
C	0.319325	0.021904	14.57867	0.0000

R-squared	0.898335	Mean dependent var	0.467385
Adjusted R-squared	0.892173	S.D. dependent var	0.005563
S.E. of regression	0.001827	Akaike info criterion	-9.704810
Sum squared resid	0.000220	Schwarz criterion	-9.545467
Log likelihood	349.5208	Hannan-Quinn criter.	-9.641445
F-statistic	145.7972	Durbin-Watson stat	1.227793
Prob(F-statistic)	0.000000		

Table 22

Null Hypothesis: RESIDUALSGINI has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=11)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.317596	0.0408
Test critical values:	1% level	-3.530030	
	5% level	-2.904848	
	10% level	-2.589907	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RESIDUALSGINI)
Method: Least Squares
Date: 08/16/15 Time: 14:13
Sample (adjusted): 1997Q4 2014Q3
Included observations: 68 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RESIDUALSGINI(-1)	-0.329637	0.136349	-2.417596	0.0185
D(RESIDUALSGINI(-1))	-0.491807	0.146026	-3.367940	0.0013
D(RESIDUALSGINI(-2))	-0.188309	0.121829	-1.545680	0.1271
C	-2.94E-05	0.000189	-0.155338	0.8770

R-squared	0.418114	Mean dependent var	2.23E-06
Adjusted R-squared	0.390838	S.D. dependent var	0.002001
S.E. of regression	0.001562	Akaike info criterion	-10.02874
Sum squared resid	0.000156	Schwarz criterion	-9.898177
Log likelihood	344.9770	Hannan-Quinn criter.	-9.977005
F-statistic	15.32907	Durbin-Watson stat	1.857402
Prob(F-statistic)	0.000000		

Table 23

Dependent Variable: DGINI
Method: Least Squares
Date: 08/16/15 Time: 14:42
Sample (adjusted): 1997Q3 2014Q3
Included observations: 69 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
D(LOG_GDPLAG)	0.124594	0.084152	1.480593	0.1437
D(LOG_CPILAG)	0.012241	0.088594	0.138170	0.8905
D(LOG_MBLAG)	0.008751	0.008752	0.999936	0.0212
D(LOG_SLAG)	0.001708	0.006859	-0.248950	0.0042
RESIDUALSGINI(-1)	-0.331045	0.116490	-2.841831	0.0060
C	-0.000422	0.000484	-0.872375	0.3863

R-squared	0.149997	Mean dependent var	0.000290
Adjusted R-squared	0.082537	S.D. dependent var	0.001707
S.E. of regression	0.001635	Akaike info criterion	-9.911051
Sum squared resid	0.000168	Schwarz criterion	-9.716781
Log likelihood	347.9313	Hannan-Quinn criter.	-9.833978
F-statistic	2.223480	Durbin-Watson stat	2.229718
Prob(F-statistic)	0.062800		

Appendix B

Figure 1 : Gini construction

A	B	C	D	E	F	G	H	I	J	K	L
# of individual	5										
Individual	**Income**										
1	520736										
2	22258241										
3	47608952										
4	84349237										
5	194046432										
6											
7											
8											
9											
10											
Mean	69756720										
	i =										
***j*=**	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	
1	0	21737505	47088216	83828501	193525696	NA	NA	NA	NA	NA	
2	21737505	0	25350711	62090996	171788191	NA	NA	NA	NA	NA	
3	47088216	25350711	0	36740285	146437480	NA	NA	NA	NA	NA	
4	83828501	62090996	36740285	0	109697195	NA	NA	NA	NA	NA	
5	193525696	171788191	146437480	109697195	0	NA	NA	NA	NA	NA	
6	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	
7	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	
8	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	
9	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	
10	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	
Vertical	346179918	280967403	255616692	292356977	621448562	0	0	0	0	0	
Horizontal Sum											1,797E+09
Gini Coefficien											0,5150958

This worksheet will let you calcuate a Gini coefficient for an income distribution with up to ten individuals.

Step One-- Input the # of individuals into cell B2
Step Two -- Input individual incomes into cells B3:B12. If # of individuals is less than 10, leave the unneeded cells blank.
Step Three --Mean income will appear in cell B13; the Gini coefficient will be reported in cell L29.

To see a Lorenz Curve of the distribution, click below on LORENZ

# of individual	5		
Individual	Income		
1	520736		
2	22258241		
3	47608952		
4	84349237		
5	194046432		
6	0		
7	0		
8	0		
9	0		
10	0		
Total	348783598		
Population Share	Cumulative Income	Cumulative Share	Perfect Equality
0	0	0	0
0,2	520736	0,00149301	0,2
0,4	22778977	0,06530977	0,4
0,6	70387929	0,20180975	0,6
0,8	154737166	0,44364806	0,8
1	348783598	1	1
ONWAAR	ONWAAR	ONWAAR	ONWAAR
ONWAAR	ONWAAR	ONWAAR	ONWAAR
ONWAAR	ONWAAR	ONWAAR	ONWAAR
ONWAAR	ONWAAR	ONWAAR	ONWAAR
ONWAAR	ONWAAR	ONWAAR	ONWAAR

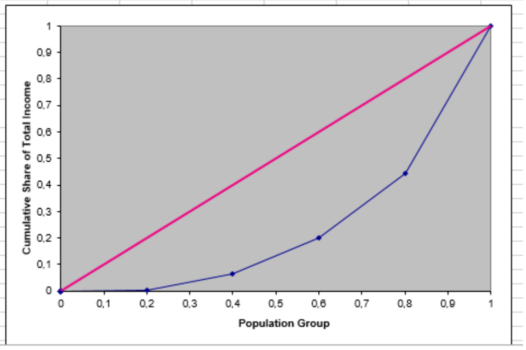

Figure 7:

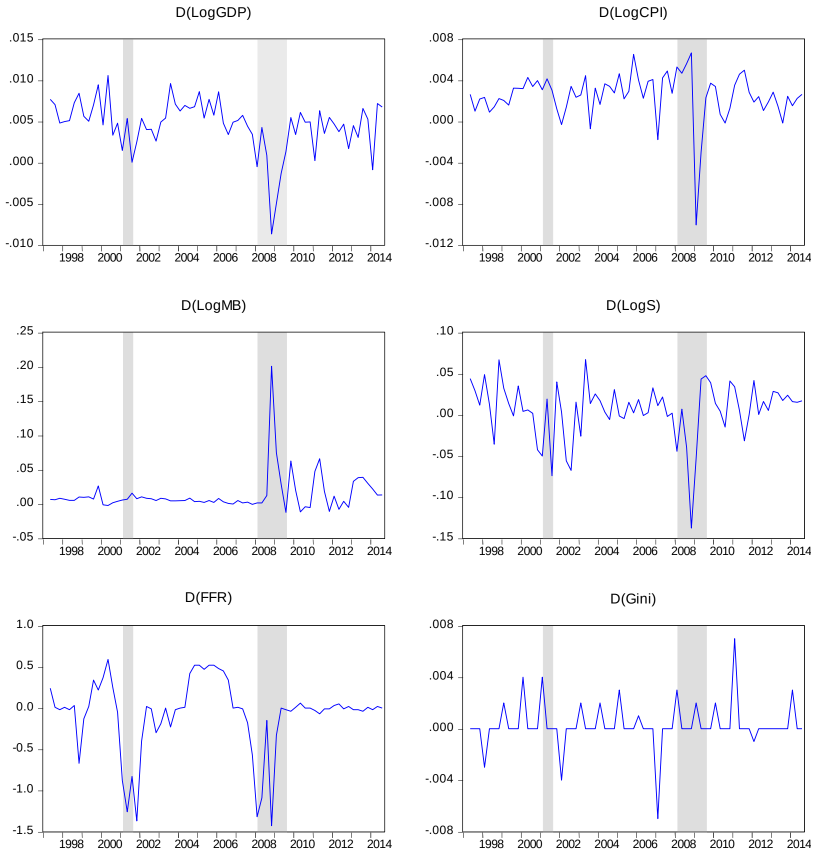
D(LogGDP)
.015
.010
.005
.000
-.005
-.010
1998 2000 2002 2004 2006 2008 2010 2012 2014
D(LogCPI)
.008
.004
.000
-.004
-.008
-.012
1998 2000 2002 2004 2006 2008 2010 2012 2014
D(LogMB)
.25
.20
.15
.10
.05
.00
-.05
1998 2000 2002 2004 2006 2008 2010 2012 2014
D(LogS)
.10
.05
.00
-.05
-.10
-.15
1998 2000 2002 2004 2006 2008 2010 2012 2014
D(FFR)
1.0
0.5
0.0
-0.5
-1.0
-1.5
1998 2000 2002 2004 2006 2008 2010 2012 2014
D(Gini)
.008
.004
.000
-.004
-.008
1998 2000 2002 2004 2006 2008 2010 2012 2014

Figure 3 : Income variables FMLI

INTEARNM:	During the past 12 months, what was the total amount of income from interest on savings accounts or bonds received by ALL CU members?
FININCX:	During the past 12 months what was the total amount of regular income from dividends, royalties, estates, or trusts earned by ALL household members?
INTERARNX:	During the past 12 months what was the total amount of regular income from interest on savings accounts or bonds earned by ALL household members?
WELFAREX:	During the past 12 months, what was the total amount of income from public assistance or welfare, including money received from job training grants such as Job Corps, received by ALL CU members?
OTHRINCX: / OTHRINCB (Bracket) / OTHERINCM	During the past 12 months, what was the total amount of other money income, including money received from cash scholarships and fellowships, stipends not based on working, or from the care of foster children, received by ALL CU members?
FSMPFRXM	Total amount of income received from self-employment income Income Imputation by family grouping, mean of imputation iterations FSMPFRXM
FINCBTAX	Amount of CU income before taxes in past 12 months (INTRDVX, INTRDVBX, ROYESTX, ROYESTBX, OTHREGX, OTHREGBX, WELFAREX, WELFREBX, RETSURVX, RETSRVBX, NETRENTX, NETRNTBX, OTHRINCX) *L
FSALARYM	Amount of wage and salary income, before deductions, received by all CU members in past 12 months (sum SALARYXM from MEMB file for all CU members)
PENSIONX / PENSIONB (Bracket)	During the past 12 months, what was the total amount of income from pensions or annuities from private companies, military, Government, IRA, or Keogh received by ALL CU members?
INTRDVXM	Amount of income received from interest and dividends, mean Income Imputation of the iterations

ROYESTX	Range that best reflects the total amount received in royalty income or income from estates and trusts during the past 12 Months