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Micro Level Data for Macro Models: The Distributional Effects of Monetary Policy.*

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Abstract

In this paper, we investigate the effect of the ECB's standard and non-standard monetary policy on income inequality in Italy. We use a novel database founded on the micro-level survey data on Income and Living Conditions (EU-SILC, Istat) in a repeated cross-section experiment, which enables us to compute measures of inequality and the distribution for different incomes and subgroups of individuals. The identification strategy is based on the interest rate surprises estimated around the ECB announcements and collected daily in the Euro Area Monetary Policy Event-Study Database (EA-MPD). Using a wide range of Local Projections, we evaluate the impact of monetary policy by comparing the performance of the impulse response functions of our inequality measures in different policy scenarios. The main findings show that over the period 1999q1-2017q4, an expansionary monetary policy compressed income inequality. These effects are heterogeneous among incomes; while the standard monetary policy affects primarily disposable income, the non-standard monetary policy has a long-lived impact on labour income distribution. After the first period, the non-standard monetary policy raises inequality of financial incomes and financial wealth benefitting mainly the top percentiles of the distribution. Our evidence suggests that quantitative easing (QE) is associated with a decrease in Italian households' inequality.

Keywords: Income Inequality, Monetary Policy, Local Projections, Survey Data, High-Frequency Data.

JEL Codes: C81, D31, E52, E58

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1 Introduction

The literature and practice of monetary policy in Europe have generally ignored the impact of conventional and unconventional monetary policy on inequality over time, but recently there has been an increase in attention to this topic. In the aftermath of the global financial crisis, central banks have used monetary policy in an unprecedented way; on the one hand by reducing rapidly the official discount rate and on the other by adopting unconventional measures to pursue price stability and sometimes to favour economic recovery through expansionary policies. There are growing concerns that the current accommodative monetary policy stance in many advanced economies may negatively affect income and wealth distribution (Acemoglu and Johnson 2012, Stiglitz (2016)). *«Those concerns have focused in particular on the side effects of monetary policy and its distributional consequences: between savers and borrowers, weaker and stronger countries, the rich and the poor. The question, in short, is whether there is a trade-off between stability and equity».* (Draghi, President of ECB, DIW Europe Lecture, Berlin, 25 October 2016). On the contrary, according to Bernanke (2015), monetary policy is not a key driver of increased inequality, as it is "neutral" or nearly so in the longer term, meaning that it has limited long-term effects on "real" outcomes like the distribution of income and wealth. Despite the large debate on the topic, the empirical literature is sometimes ambiguous with mixed conclusions and still scarce evidence, which is due to the lack of micro-level data that enable one to compute inequality measures for a long period at the household or individual level.

In the present study, we investigate whether monetary policy, both conventional and unconventional, has affected income inequality in Italy, by focusing on survey data on household income disaggregated at the quarterly level. Inspired by the recent strand of literature using household-level data, (Coibion et al. (2017) and Montecino and Epstein (2015) for the US, Mumtaz and Theophilopoulou (2016) for the UK, Saiki and Frost (2018) for Japan and Guerello (2017), Lenza and Slacalek (2018) for the euro area) and Casiraghi et al. (2018) for Italy, we combine microdata on disposable income, earnings, financial capital income, and financial wealth with a macro model to estimate the effects of monetary policy on *ad hoc* inequality indices calculated at the individual household level.

In doing so, our contribution is twofold: we use the EU-SILC microdata on Italian households and living conditions (Istat) exploiting the survey for the first time in a repeated cross-sectional dimension to build inequality measures over time and for specific incomes and wealth (disposable income pre and post transfers, labour income, financial capital income, financial wealth) and subgroups of individuals (borrowers vs. savers, employees vs. self-employed workers). As the survey starts in 2003, we require a wider time span of the series to cover the entire period of the ECB communications, which began in 1999. Specifically, we extended the series backwards to 1999, by using the microdata from the Historical Archive of the Bank of Italy's Survey of Household Income and Wealth (SHIW).

Additionally, we adopt a new identification strategy for monetary policy shocks: we use the euro area Monetary Policy Event-Study Database (EA-MPD) by Altavilla et al. (2019) which presents high-frequency data for the intraday changes around the ECB policy announcements of Overnight Index Swap (OIS)[1] at different maturities (OIS 1-month and OIS 10-years). The identifying assumption is that within the day monetary policy does not react to asset prices, and therefore causality goes from monetary policy to asset prices. Following Romer and Romer (2004) and Miranda-Agrippino and Ricco (2021), we want to isolate as much as possible, the monetary policy surprises at the quarterly level from other macroeconomic and information shocks embedded in the ECB policy announcements. To cope with predictability, we purged the monetary policy rate changes from the ECB quarterly forecasts of GDP, inflation, and unemployment from the Survey of Professional Forecasters.

Finally, using a wide range of Local Projections (Jordà (2005), Coibion et al. (2017), Furceri et al. (2018)), we evaluate the impact of monetary policy on inequality by analyzing different policy scenarios reflecting the effects of conventional monetary policy (a shock to

[1] OIS are euro area-wide interest rate measures, not affected by country risk either as credit risk or as safe haven premia. The OIS contracts are over-the-counter interest rate swaps where the underlying reference rate is the euro area inter-bank rate, EONIA. Unlike US Federal Funds Futures, which have fixed calendar month coverage, each OIS contract is fixed maturity.

OIS 1-month) and of unconventional monetary policy (a shock to OIS 10-years). To evaluate the effects on inequality, we focus mainly on two distributional channels – macroeconomic and financial – through which monetary easing may have opposite effects on income inequality. Monetary expansion stimulates output and job creation benefiting low and middle-income households and reducing income inequality. At the same time, lower interest rates lead to higher asset prices and capital returns; this can increase income inequality by making rich households better off. The macroeconomic channel is represented by GDP, employment, and wages which reflects the composition of household income, while the financial channel is represented by excess bond premium, share prices, and spread between long- and short-term rates. Furthermore, exploring the EU-SILC dataset we consider two additional channels: the saving composition channel which allows us to evaluate the impact on inequality between borrowers and savers (people with and without financial constraints), and the earnings heterogeneity channel (we refer to it improperly since we do not include the newly employed) which allows us to assess the effect of monetary policy on employees and self-employed workers.

However, Gini coefficients and other inequality measures are sampled annually, while macroeconomic and financial variables are sampled quarterly. To address this mixed-frequency problem, we follow an approach of temporal disaggregation adopting the Chow-Lin technique in Quilis (2013), which allows us to transform low-frequency data (annual data) into high-frequency data (quarterly data). For each series of inequality measures, we have a longer time span from 1999q1 up to 2017q4.

Our main findings show that over the period 1999q1-2017q4, an expansionary monetary policy shock mainly compressed the inequality of Italian households, particularly with conventional monetary policy. The income composition channel works in the right direction after an unconventional monetary policy shock since inequality of disposable and labour income (in particular that of employees) reduces. An equalizing effect is also evident when we consider the response of disposable income before social transfers (pension excluded), meaning that fiscal policy did not have a crucial redistributive role in Italy during the crises and the recovery period. Looking at the subgroups of individual households, an expansionary monetary policy is equalizing for "savers" in the short term due to higher asset prices. While inequality increases for "borrowers" on impact and then reduces due to prolonged lower interest rates on mortgages. Overall, these effects are heterogeneous and they primarily benefit the bottom of the income distribution, particularly that of labour income.

Unlike the US and the UK, we also found that the impact of the financial channel has an ambiguous effect favouring wealthy households only in the medium run. The top 1% gets the higher benefits. In the long run, the persistent decline of the Gini index of financial wealth reflects some gains at the bottom of the distribution supporting the idea that equity prices were not the main drivers of rising inequality in Italy. Overall, our evidence suggests that QE is associated with a decrease in inequality in Italian households, although the impact of the effects is modest.

The remainder of the paper is organized as follows. Section 2 describes the EU-SILC database and the methodology for the construction of measures of inequality and the distribution of income and financial wealth. Section 3 focuses on a new identification strategy based on daily monetary surprises. Sections 4 and 5 outline our empirical design, based on the local projection technique augmented with additional controls to assess the effects of both conventional and unconventional monetary policy shocks. Furthermore, it illustrates and interprets the main empirical results and robustness checks. Section 6 concludes.

2 The Measure of Inequality for the Italian Incomes Distribution

In this section, we briefly describe the Italian Survey on Income and Living conditions and the construction of measures of inequality and the distribution of total disposable income, labour income, financial capital income, and financial wealth.

2.1 The Italian Statistics on Income and Living Conditions (EU-SILC)

The measures of income and wealth inequality are all constructed using The European Union Statistics on Income and Living Conditions (henceforth, EU-SILC), which is a survey aiming at collecting a large set of qualitative and quantitative information at individual and household levels in member countries (Statistics on Income and Living Conditions. Regulation of the European Parliament. No. 1177/2003). It provides some crucial indicators of income, poverty, and social exclusion in the European Union (i.e., at risk of the poverty rate and the Gini coefficient). It has been carried out yearly in different EU countries since 2004 and it is the reference source for comparative statistics on income distribution in Europe. The survey also provides both cross-sectional and longitudinal data comparable across the participating European countries. It is conducted through household and personal interviews (all individuals over 16 years of age). The sample design is based on a two-stage scheme (municipalities and households), where the primary sample units (municipalities) are stratified by population size within each region. Italy, like most EU countries, adopted a rotational sample design, composed of four rotational groups, each to be investigated for four years. Each year one-fourth of the sample is renewed. The overall sample is statistically representative of the population residing in Italy which is about 20,000 households per year. In particular, in 2018, it amounted to 21,173 households (39,969 individuals), residing in about 680 municipalities.

Data collection is structured in three parts: a. General form to collect demographic information related to each household member (sex, date, place of birth, citizenship, etc.) and some information for each household member aged less than 16 years (the type of school attended, formal and informal childcare, etc.); b. Household questionnaire to collect information about housing conditions, housing expenses, economic situation, material deprivation, and household income components; c. Personal questionnaire for each household member aged at least 16 years to collect information on education, health, current or previous labour, and income by detailed components (employee, self-employment, pensions and other social transfers, financial and real capital, private transfers). Income and social benefits data collected from interviews are integrated with administrative register data, generally fiscal data, to improve the quality of statistical information.[2] Overall, all EU-SILC quantitative information is processed by using specific statistical procedures to delete outliers and impute missing data.[3]

In our dataset, we matched all parts of the questionnaires, taking into account demographic information, household income components, information on education, health, current or previous labour, and, income broken down by components. Although not explicitly designed to measure wealth, the EU-SILC survey contains information on multiple sources of financial wealth. Following the OECD Household financial assets classification,[4] we derive a measure of financial wealth by summing the estimated amount held by households in four different components: currency and deposits, public bonds, shares, and other bonds and equities, mutual funds, and other assets. Finally, the dataset includes cross-sectional microdata for Italian individual households stacked from 2004 up to 2018. Overall, we collected more than 640 thousand individual records over 15 years.

2.2 Measuring Inequality

The detailed microdata at hand does allow us to consider a wide range of inequality measures concerning the total disposable income before and after transfers, labour earnings broken down by salaries from employees and income of self-employed workers, financial capital

[2] Detailed information in Törmälehto and Jäntti (2013).
[3] For further details see Istat (2008).
[4] National Accounts of OECD Countries, 2019.

income[5] and financial wealth[6]. These are the variables we consider in our analysis. Income variables are available at the annual frequency and refer to the year before the survey (12 months before the interviews). The EU-SILC provides information on net incomes however, starting from 2007, gross incomes are available as well. For the sake of homogeneity, in our analysis we consider net incomes, taking into account that since 2007 no relevant change has occurred in tax rates and income brackets. However, as a further extension, we can compute inequality measures of total disposable income before social transfers to evaluate the impact of conventional and unconventional monetary shocks by isolating as much as possible the automatic stabilization effects of the transfer system. Furthermore, we can compute *ad hoc* inequality measures for some subgroups of individuals, i.e. borrowers vs. savers, exploiting the rich information set on individual characteristics.

We exclude incomplete income records and use the weights provided within the survey in order to compute inequality measures reflecting the Italian population structure. All nominal variables have been expressed in real terms (2015 prices) using the annual aggregation of the Harmonised Index of Consumer Prices (HICP).[7] To adjust household income according to the household size, we use the modified OECD equivalence scale, and then we assign the equivalent household income to each member of the household, which is divided by the number of household members converted into equivalized adults. In other words, we assume an equal intra-household division of income and approximate individual living standards by assigning each individual the equivalized household income.[8] In doing so, we can control for

[5]Total disposable income is given by the sum of the earnings and financial income plus the one arising from other sources, such as transfers (unemployment benefits, pensions, children allowances etc.), income from the rental of a property or land (after deducting costs such as mortgage interest repayments) minus taxes on income and social insurance contributions. Disposable income before transfers is given by the disposable income minus social transfers described above excluding old-age and survivor's benefits. Financial income is defined as the sum of incomes, which refers to the amount of interest or capital gains from assets such as bank accounts, certificates of deposit, bonds, etc, dividends and profits from capital investment in an unincorporated business (less expenses incurred).

[6]Financial wealth is an estimate of the number of different assets (accounts and deposits, public bonds, securities, shares, mutual funds, and other assets) held by individual households.

[7]Eurostat, 2018b. Harmonised Index of Consumer Prices (HICP).

[8]Household members are equivalized or made equivalent by weighting each according to their age, using the so-called modified OECD equivalence scale. This scale gives the following weight to household members: 1.0 to the first adult; 0.5 to the second and each subsequent person aged 14 and over; 0.3 to each child aged

the number of adults and the number of children in the household.

Following Casiraghi et al. (2018), we consider mainly three measures of inequality: the Gini coefficient, the ratio between the 90th percentile and 10th percentile, and the ratio between the 75th percentile and 25th percentile. Additionally, we compute the 10th, 25th, 50th, 75th, 90th, and 99th percentiles for all the variables considered above. We construct these measures for all the definitions of income and wealth. Taken together, these are extremely valuable because they provide a complete overview of inequality, its distribution, and its dynamics. Moreover, concerning the US CEX survey, which does not include the very upper end of the income distribution (i.e., the top 1%) which has played a considerable role in income inequality dynamics since 1980 in the US and Europe, the EU-SILC includes even incomes at the top end of the distribution. Even though the tails of the distribution are likely to contain some measurement errors, we decided not to trim them. Since all income and wealth information refers to the previous year, automatically the EU-SILC inequality measures series shifts back one year, precisely from 2003 to 2017.

However, to cover the entire period of ECB communications, starting in 1999, we need a longer time span of the series, because the survey, alone, starts in 2003. As a first step, we compute a back-calculation of EU-SILC inequality income measures using the microdata from the Historical Archive of the Bank of Italy's Survey of Household Income and Wealth (SHIW). Specifically, we extended the series backwards until 1999, in such a way that it is possible to recover 19 observations for each inequality measure.

The SHIW has been carried out by the Bank of Italy since the mid-1960s and comprises about 8,000 households per year distributed over 300 Italian municipalities and provides information on individual household characteristics and their balance sheet (incomes and wealth).[9] Baffigi et al. (2016), extensively examines how survey data are related to those coming from other sources (national accounts, tax data, censuses, other sample surveys such as EU-SILC, and so on), summarizing the main results of the numerous works carried out on this

under 14.

[9]SHIW Archive, Bank of Italy.

aspect.[10] The authors found that both SHIW and EU-SILC exhibit bias due to nonresponse and underreporting. They also found that the average household income and the Gini inequality index exhibit a sharp correlation between the two surveys, even if there are some differences in the calculation of some aggregates, such as those concerning self-employment or financial capital incomes.[11] The overall estimates obtained in the EU-SILC survey can be used for comparison with the corresponding SHIW measures with consistent results. Due to the few observations of the EU-SILC series, it was difficult to identify a historical pattern for each index and use it to backcast the series using ARIMA models. Thus, for each pair of inequality measures and percentiles of the distributions, we compute coefficients by comparing one value to another over the two surveys' common spans. Then using those coefficients, we retropolate the EU-SILC inequality indexes of each income variable. Finally, we obtain a longer period of yearly data from 1999 to 2017 useful for the macro-model aimed at estimating the effect of both conventional monetary policy and unconventional monetary policy actions. Specifically, the latter includes the zero lower bound period starting from the last quarter of 2012. Figure 1 shows the dynamics of different measures of inequality we have extrapolated backwards for various components of income and financial wealth. Overall, all measures show slightly increasing dynamics over the last eighteen years in Italy. Financial capital income exhibits more volatility compared to disposable and labour income, especially during and after the financial crises. In the last three years, the financial inequality index shows a slight decrease, quite similar to the labour income inequality dynamics.

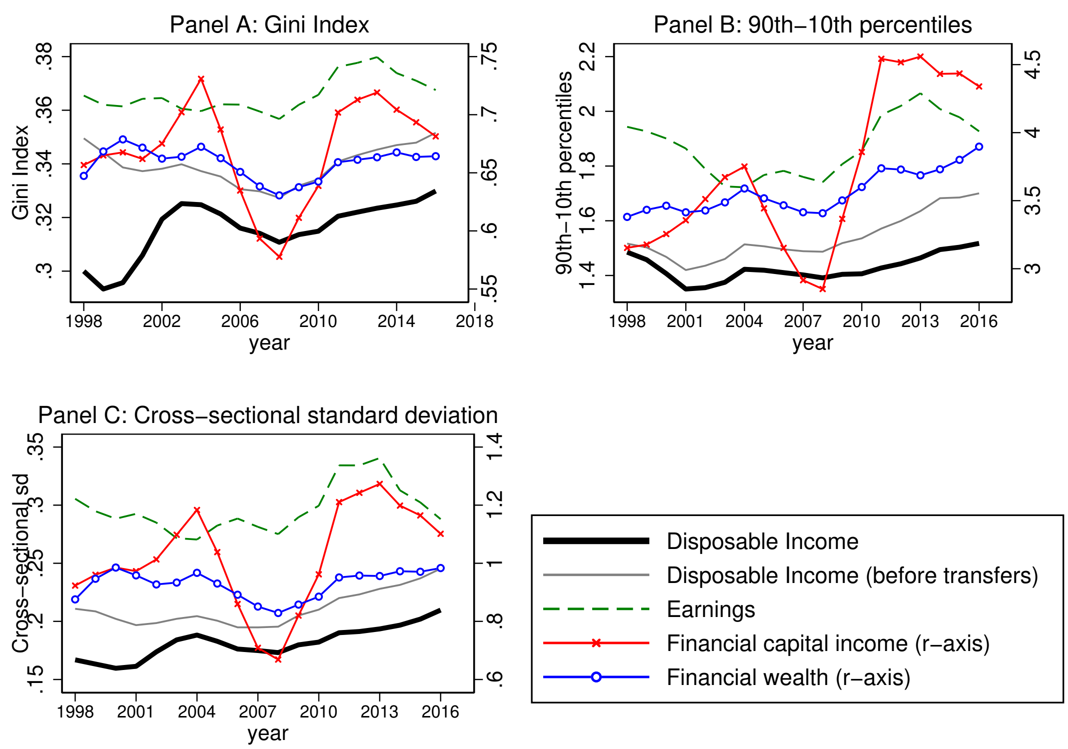
3 The identification Strategy of Monetary Policy Shocks

In order to characterize the effects of both conventional and unconventional monetary policy on the income distribution of individual households, we use the monetary policy surprises

[10]Following this strand see also Jappelli and Pistaferri (2010) and Fagereng et al. (2016).

[11]In the EU-SILC survey, the income from self-employment coming from interviews is compared with that from administrative sources and the maximum of the two values is imputed in the estimate of household income. A similar procedure is adopted for financial capital incomes.

Figure 1: Measures of Income and Wealth Inequality. Moving Averages. Years 1998-2017.



Note: Author's calculations using the EU-SILC survey (Istat).
See Section 2.2 for details.

collected in the euro area Monetary Policy Event-Study Database, (EA-MPD, henceforth) by C. Altavilla, L. Brugnolini, R. Gürkaynak, R. Motto and G. Ragusa, henceforth ABRGM.

In their work, ABGRM estimate latent factors from changes in yields (i.e., the Overnight Index Swap) in such a way as to provide structural interpretation. In particular, they identify four monetary policy factors, labelling as Target, Timing, Forward Guidance (FG), and QE. It turns out that financial markets perceive a short-term and longer-term forward guidance factor. They call "timing" the first factor, which has a peak effect at about the six-month maturity and has little effect on long-term interest rates, to differentiate it from what is now commonly called forward guidance, which has a peak effect at two years and significantly affects long-term interest rates. While the Timing factor captures the shifts in market expectations over the next few meetings that leave longer-term interest rates essentially unchanged, the Forward Guidance factor captures the revision in market expectations about the future path of policy rates that are orthogonal to the current policy surprise. The QE factor has a larger effect the longer the maturity is, consistently with QE implementation in the euro area, where the average maturity of purchased securities was about eight years. Importantly, QE turns out to have lowered all yields and narrowed spreads, Italians included.

For our purpose, the following policy rate changes in basis points around the ECB announcements over the period 1999-2017 are considered: OIS 1-month and OIS 6-months, which are the monetary instruments that allow us to identify mostly the effect of conventional monetary policy because, following the analysis by ABGRM, they are consistent with the dynamic of Target and Timing factor loadings, respectively; OIS 2-years and OIS 10-years are the rates that mostly identify the effects of unconventional monetary policy because they are consistent with the dynamics of Forward Guidance and QE factor loadings, respectively.[12] The identifying assumption is that within a day monetary policy does not react to asset prices, and therefore causality goes from monetary policy to asset prices.

The selected OIS changes identify periods in which monetary policy was more expansionary

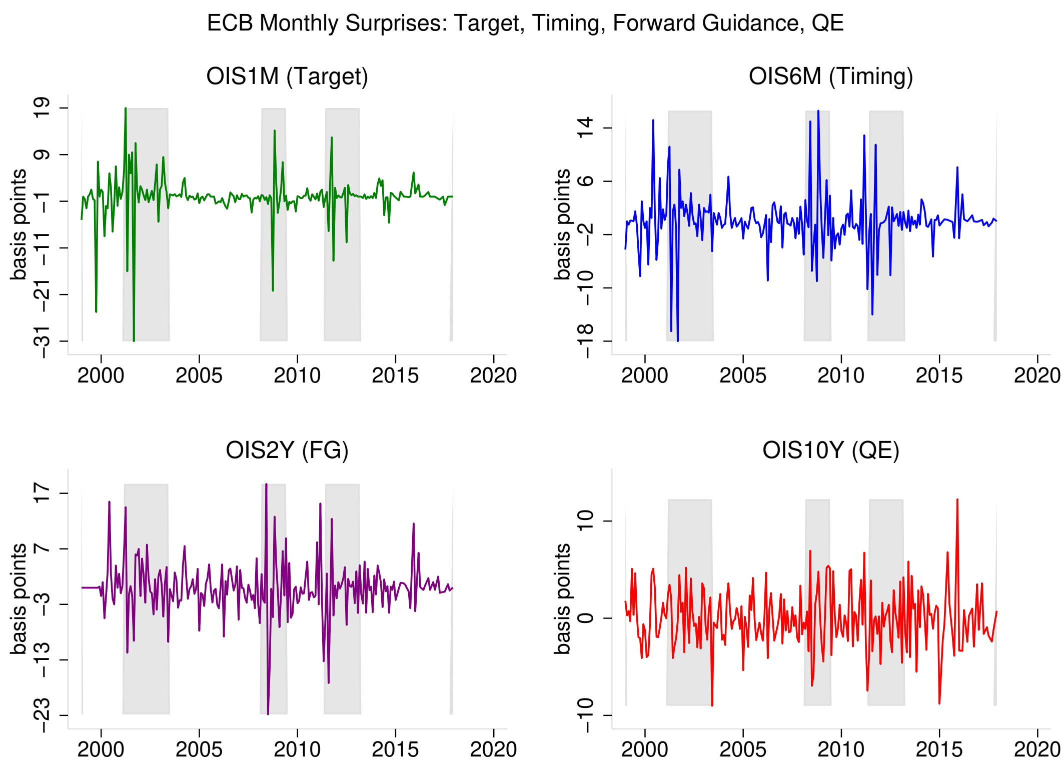
[12]For an accurate description of the methodology, see the Appendix to *"Measuring euro area Monetary Policy"* by Altavilla et al. (2019).

than usual (conditional on real-time forecasts), especially after 2001 when the national currencies were completely converted to the Euro. Against the risk of deflation, 2002-2005 is identified as a period of consistently positive MP shocks. On the other hand, the 2006-2008 period is identified as the most restrictive since the creation of the euro area. After the 2008-2009 financial crises, central banks have aggressively cut monetary policy rates, in many cases, to their lower bound. In contrast, the European Central Bank did not immediately cut its main policy interest rate to zero. The rate on the main refinancing operations (MRO) was reduced sharply at the end of 2008 reaching a low of 1% in May 2009, but not falling below that level until mid-2012. Interest rates were further reduced after the intensification of the sovereign debt crisis and during the following economic crisis. The rate on the deposit facility reached zero in July 2012, before entering negative territory from 2013 onwards.

Since the 2008-2009 financial crisis, in addition to the so-called standard monetary policy, the ECB implemented several additional purchasing programmes (Securities Market Program, SMP and the Outright Monetary Transactions, OMT) and longer-term refinancing operations (LTROs) designed to support dysfunctional market segments, foster bank liquidity, and avert a credit crunch. In September 2014, the ECB announced the purchase of asset-backed securities and a broad portfolio of euro-denominated covered bonds. To re-anchor inflation expectations on inflation rates below, but close to 2%, and to inject liquidity into the system, on the 22nd of January 2015, the Governing Council of the European Central Bank decided to launch an expanded asset purchase programme. They joined other central banks in adopting quantitative easing, in addition to other non-standard monetary policy measures as the margin for standard monetary policy changes in the form of interest rate cuts had eroded. All the non-standard monetary policy measures were embedded in the Forward Guidance, which means that the ECB has been providing information about its future monetary policy intentions based on its assessment of the outlook for price stability.[13]

[13]The ECB began using Forward Guidance on July 4, 2013, when *"The Governing Council expects the key ECB interest rates to remain at present or lower levels for an extended period of time."*

Figure 2: OIS Rate Changes Around the ECB Monetary Policy Announcements Aggregated Monthly with Recession Dating (shaded area).



Note: Author's calculations based on EA-MPD dataset.

In our empirical analysis $\epsilon_t^{MP_i,m}$ describes the rate changes that we are going to use separately in four different scenarios, where MP_i = OIS1M, OIS6M, OIS2Y, OIS10Y and m indicates that the variables are monthly (Figure 2).

To better concentrate on the primary mechanisms that a monetary policy shock activates, we first assess the influence of monetary policy on Italian macroeconomic variables on a quarterly basis (without inequality measures), by comparing conventional and unconventional scenarios. To this aim, we aggregate the original variables by summing the monthly series of rate changes into quarterly series $\epsilon_t^{MP,q}$.

However, the OIS changes proposed as monetary surprises for the identification have two main issues. First, they are predicted by past information of other macro variables and autocorrelated with their past. Second, there is a potential information problem since central banks transfer information about the outlook of the economy around policy announcements. Thus, it is difficult to disentangle a pure monetary policy surprise from one that arises, for instance, from the central bank information (Miranda-Agrippino and Ricco (2021)). This issue is even more concerning once we aggregate the monthly measures into a quarterly one. To be confident that the $\epsilon_t^{MP,q}$. series are actually unanticipated, i.e., orthogonal to other macroeconomic variables, following Miranda-Agrippino and Ricco (2021) we regress the monetary rate changes onto the ECB Survey of professional forecasters on GDP, inflation and unemployment at a quarterly level[14]. The Survey of Professional Forecasters (SPF) is available from 1999q1 and shows forecasts over time very similar to the ECB forecasts. Specifically, we regress OIS1M, OIS6M, OIS2Y, and OIS10Y, one at a time, on five sets of regressors: forecast on GDP, inflation and unemployment for the current year (SFPcurr), for the next year (SFPnext), the forecast 1 year ahead (SFP1), 2-years ahead (SFP2), and the 1-year

[14]The ECB Survey of Professional Forecasters (SPF) collects information on the expected rates of inflation, real GDP growth and unemployment in the euro area at several horizons, ranging from the current year to the longer term. The Survey of Professional Forecasters began in 1999. The aggregate results are published four times a year.

forecast revisions (SFP2), and take the residuals representing purged-OIS changes.

$$\epsilon_t^{MP_i,q} = \alpha SPFcurr_{j,t} + \beta SPFnext_{j,t} + \gamma SPF1Y_{j,t} + \delta SPF2Y_{j,t} + \lambda SPFrev_{j,t} + \eta_t^{MP_i,q} \quad (1)$$

where $j = (GDP, inflation, unemployment)$. Furthermore, before estimating the impulse response functions (IRFs), we verify that the purged-OIS changes are not auto-correlated with their past. These issues are particularly concerning in the context of a local projection in which the measure is included directly (and not as an instrument) and thus might lead to biased (and puzzling) results, as shown in Miranda-Agrippino and Ricco (2021). As expected, rate changes do not exhibit any relevant auto-correlation, implying that we are isolating potential information problems about the outlook of the economy, as much as possible in a short temporal window[15]. Then, we project our purged-OIS changes, named our monetary surprises, onto endogenous variables, one by one to estimate the impulse responses of standard and non-standard monetary policy scenarios separately.

4 The Empirical Model

Along with the four direct measures of the monetary policy stance $\epsilon_t^{MP_i,q}$ purged of anticipatory effects, we want to investigate how monetary policy affects the Italian economy focusing on the macroeconomic and financial transmission channels (i.e., higher asset prices have a positive effect on capital income held by the wealthier while an increase in GDP, by expanding employment, could have a positive effect on labour income, offsetting the total effect on inequality). To this aim, additional macroeconomic variables are considered in the analysis, namely real GDP, the GDP deflator in first difference, employment from the Eurostat database, and the share price index for Italy from the FRED St. Louis dataset. Furthermore, to fully identify all the transmission channels of monetary policy, we include

[15]Test of orthogonality (Forni and Gambetti (2014)) with respect to the lagged values of the purged-OIS are available on request.

a proxy of the excess bond spread (BBB) estimated by Jarociński and Karadi (2020) to capture financial conditions in a conventional monetary scenario, as no excess bond premium measure is available for the euro area. We aggregated at the quarterly level the monthly BBB bond spread available over the period 1999q1-2016q4 and extended it up to the 2017 quarters.[16] We also include an additional spread variable measured as the difference between long- and short-term interest rates from the ECB database (i.e., 10-year government bonds minus 3-month rate). Finally, we include the house prices to control also for the collateral effect of monetary policy and the hourly wages from the Eurostat database to account for earnings heterogeneity. We use all the macroeconomic variables in log-level percentage points except for the excess bond premium and the spread which are in basis points; GDP, share prices, and wages are also expressed in real terms. All variables are available at a quarterly frequency over the period 1999q1-2017q4. Thus, in our model, the list of endogenous variables is the following:

$$Y_t = [gdp_t, gdpdefl_t, employment_t, ebp_t, shareprice_t, spread_t, houseprice_t, wages_t] \quad (2)$$

The conventional monetary policy effects are evaluated using alternatively the monetary surprises purged-OIS1m and -OIS6m which gauge mainly the conventional policy effects, whereas the non-standard monetary policy effects are separately captured by purged-OIS2y and -OIS10y. As we continue to experience surprises in short-term rates since 2013, when unconventional monetary policy was established, all policy scenarios are calculated throughout the complete sample from 1999Q1 to 2017Q4, which also includes the QE stance of monetary policy since the quantitative easing is active mostly from 2014 onwards.

To compute the impact of monetary policy, we estimate impulse responses on a quarterly basis with local projections (LP) along the lines of Jordà (2005), whose flexibility allows us to deal with a small sample size[17]. Implementing the VAR methodology with short series would

[16] For the sake of comparison, we maintain this variable also in the assessment of a non-standard scenario while being aware that the excess bond premium is no longer informative in this latter case.

[17] A recent paper by Plagborg-Møller and Wolf (2019) demonstrates that LP and VAR estimators are

preclude recursive estimation and could yield bias and inconsistent results. This methodology was introduced to address the potential misspecification problem in VARs. As Ramey (2016) stressed, if the VAR adequately captures the data-generating process, this method is optimal at all horizons. However, if the VAR is misspecified, then the specification errors will be compounded at each horizon. The LP approach consists in running a sequence of predictive regressions of a variable of interest Y on a structural shock and meaningful control variables for different prediction horizons (h) without casting the Wold representation.

The three main advantages of this methodology are the following.[18]

i. Unlike VARs, the LP method does not impose any underlying dynamics on the variables in the system.

ii. The technique is more robust to misspecification.

iii. Does not suffer from the curse of dimensionality inherent to VARs, and can more easily accommodate non-linearities, such as state and sign dependencies.

As the Jordà method for calculating impulse response functions imposes fewer restrictions, estimates are often less precisely estimated and are sometimes erratic. Keeping in mind its strengths and weaknesses, the model we estimate is the following:

$$\begin{gathered} Y_{t+h} = \alpha^{(h)} + \Sigma_{i=1}^{I} \psi_i^{(h)} Y_{t-i} + \beta^{(h)} \epsilon_t^{MP,q} + \eta_{t+h} \\ \eta_{t+h}^{(h)} \sim N(0, \Sigma_\eta^{(h)}) \quad \forall \quad h = 1, \ldots, H \end{gathered} \tag{3}$$

where Y_{t+h} represents the left-hand side endogenous variables with four lags up to horizon h, $\alpha^{(h)}$ is a constant, Y_{t-i} is the control set with i lags and the corresponding estimated coefficients $\psi_i^{(h)}$, and η_{t+h} are the residuals. As a benchmark, we set I=4. We used alternatively two sets of control variables, which are potentially important given the relatively short sample periods:

two-dimension reduction techniques with common estimands but different finite-sample properties.

[18]For further information, we refer to Miranda-Agrippino and Ricco (2021), Ramey (2016), Kilian and Kim (2011) Marcellino et al. (2006), amongst others.

one for the estimate of the impulse response functions in the conventional scenario that embodies all the lagged values of the dependent variables excluding the spread (which reacts mainly to unconventional policies). And the other set of variables for the unconventional scenario includes all the lagged values of the dependent variables excluding the excess bond premium (which reacts mainly to conventional policies) and including the spread. We don't include additional lags of the shock $\epsilon_t^{MP,q}$, as the sample autocorrelation function for each monetary surprise doesn't reveal a significant correlation between different lags, and since the inclusion of these would imply dropping observations.[19]

The estimated coefficients $\hat{\beta}^h$, for $h = 0, ..., H$ represent the effects of the monetary policy shocks $\hat{\epsilon}_t^{MP,q}$, alternatively conventional and unconventional, at time t on the macroeconomic aggregates Y_{t+h} considered at time $t + h$.[20] As shown by Jordà (2005), the direct estimation of the autoregressive coefficients $\beta^{(h)}$, for $h = 0 \dots 16$, corresponds to the estimation of the impulse response functions. Hence, the IRF is given by the sequence of regression coefficients of the structural shock and is consistent with asymptotic normality properties. The impulse responses are presented in the next section with 1 standard deviation confidence bands. The residuals $\eta_{t+h}^{(h)}$ arising from this projection are vector moving average (VMA) processes of order h. As they are a combination of one-step-ahead forecast errors except for $h = 0$, they are serially correlated and heteroskedastic. In other words, they are consistent but less efficient. To address this issue, the author suggests estimating the variance-covariance matrix $\Sigma_\eta^{(h)}$ using the Newey-West (1987) heteroskedasticity and autocorrelation consistent estimator (HAC).

[19]While a vector autoregressive model (VAR) consumes data only along time with the lag dimension (p), LP consumes data both along the lag (p) and the lead (h) dimension, thus the lag-length selection is crucial (Brugnolini (2018)).

[20]Following the literature on monetary policy effects, it is conventional to assume that monetary policy shocks do not have contemporaneous effects on output, inflation, etc. but may have a contemporaneous effect on equity prices and spread. In our analysis this is not the case, since using quarterly aggregation, monetary policy shock may have a contemporaneous effect on all variables.

4.1 The Transmission of Conventional and Unconventional Monetary Shocks

Far from a narrow definition of conventional and unconventional monetary policy, we assess the impact of these monetary policy actions on the Italian economy using different identification strategies. First, we estimate the impact of standard monetary policy over the period 1999q1-2017q4, shocking the purged OIS1M and OIS6M, as monetary surprises related mostly to target and short-term monetary policy effects respectively. Then, we estimate the effect of non-standard monetary policy over the same sample 1999q1-2017q4, shocking the purged OIS2Y and OIS10Y as monetary surprises related mostly to Forward Guidance and QE effects, respectively. Finally, we may compare the differences between the conventional and Forward Guidance scenarios in terms of QE, because the policy rate has been at the zero lower bound (ZLB) since 2013q1 and only non-standard tools have been used. We take into account that monetary shocks may have a simultaneous influence on all macro-variables when evaluating the impact of conventional and unconventional methods.

The results are presented in Figure 3. The first and the second line refer to conventional policy (OIS1M and OIS6M shocks, respectively) and are compared with the QE impulse responses (OIS10Y shock). Over the entire sample, 1999q1-2017q4, an expansionary monetary policy shock, that is, a 100 basis points decrease of the monetary surprise, increases the Italian real GDP in the short run. The effect on employment is stronger and more persistent compared to GDP. Inflation is around zero on impact, showing thereafter upward dynamics, while on impact the impulse response of the share price index upsurges both for the OIS1M and OIS6M monetary shock. As expected, the proxy of the excess bond premium for the euro area goes down in the short run, and the spread reduces.

An expansionary non-standard policy shock increases both the Italian real GDP and employment, but is less persistent in comparison to the conventional scenario, whereas the response of prices sharply increases on impact and then remains positive. The excess bond premium slightly rises on impact and then exhibits downward dynamics, while the effect on the spread is sharply negative even in the long run. The share price index shows a less positive reaction compared to the conventional scenarios. After a QE shock, the impulse response function of house prices, differently from what we expected (Hülsewig and Rottmann (2021)), goes down on impact, but it shows increasing dynamics over the quarters. Finally, the response of wages is positive on impact and persistent throughout the period.

In the third line of Figure 3, we can gauge the specific effect of Forward Guidance over the entire sample period concerning the QE stimulus, using the purged OIS2Y as our monetary innovation. The advantage of using an interest rate longer than the targeted policy rate is that it incorporates the impact of forward guidance and therefore remains a valid measure of monetary policy stance also during the period when the federal funds rate is constrained by the zero lower bound (Jarociński and Karadi (2020)). The effect of forward guidance is similar to the conventional scenario for the GDP and the GDP deflator in fact, it seems less effective for employment. Because FG incorporated the ECB policy goals of anchoring the inflation target below but close to 2%, the impact on financial indicators is considerably different, especially for the share price index, which is larger than in the QE scenario. FG shock reduces the spread, as expected. The reaction of the latter is quite similar to the one in the QE scenario. All in all, after both a conventional and a QE stimulus, the results are in line with the bulk of the theoretical and empirical literature on monetary policy shocks, but not house prices, which is a critical issue for the Italian economy.

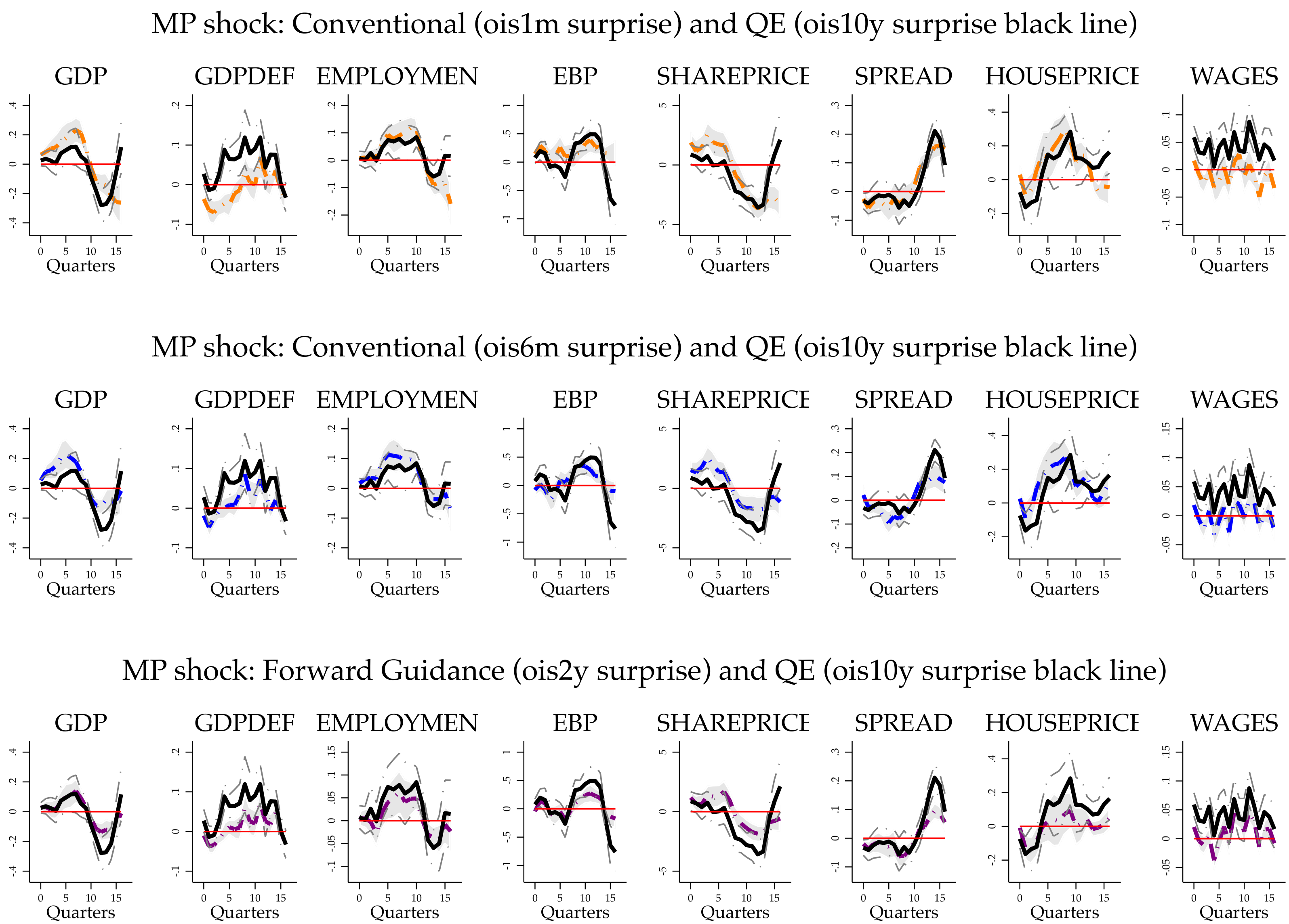
4.2 The Transmission of Monetary Shocks: Some Robustness

To verify the consistency of these results, we consider some robustness checks of our main results to different identification strategies of the monetary policy shock and the use of a SVAR methodology.

First, we use in the LP the monetary policy surprises estimated for the euro area by Jarociński and Karadi (2020)[21]. They found that the presence of information shocks

[21] They separate monetary policy shocks from contemporaneous information shocks by analyzing the high-

Figure 3: IRFs of Conventional and Unconventional Monetary Policy



Note: Impulse responses of the different macroeconomic variables to a 100 bp. expansionary monetary policy shock using the baseline LP model excluding the measure of interest $Z_{i,t}$ from the system. All the responses are in percentage points; IRFs of EBP and spread are in basis points. The dash-dotted gray lines and light-shaded areas are 68% confidence bands.

embodied in central bank communication attenuates the estimated effects of monetary policy on standard high-frequency information. Consequently, their estimates purged of this bias imply stronger monetary transmission. Responses to an expansionary monetary shock purged from information bias over the sample 1999q1-2016q4 are comparable to the QE ones (see Figure 15 in Appendix B). Some differences arise in the intensity of response: the increase in GDP, inflation, and employment is less marked in comparison to the QE impulse responses; the excess bond premium is slightly positive and persistent while the response of house prices is sharply positive even in the short run. The spread also reduces, but the effect is less evident in comparison to the QE scenario. All in all, the results seem to reinforce our choice.

Second, we identified the monetary policy shock by estimating a SVAR model with a combination of contemporaneous and sign restrictions. The identification strategy follows Weale and Wieladek (2016), and it is based on the sign restrictions presented in Table 1. It is implemented using the QR decomposition algorithm proposed by Rubio-Ramirez et al. (2010)[22].

Table 1 shows the sign restrictions we use for a positive demand shock, a positive supply shock, and a negative monetary shock, according to the literature. Instead of using assets purchase announcements, we introduce, as a monetary policy stance, the shadow short-term rate (SSR, henceforth) by Krippner (2013) in its latest version updated to 2020[23] to fully cover the entire span 1999q1-2017q4 taking into account the ZLB period around and after the global and sovereign debt crises. We apply to it a negative sign restriction representing an

frequency co-movement of interest rates and stock prices in a narrow window around the policy announcement. Their estimates are on a monthly frequency over the period 1999m1-2016m12 so we obtain a quarterly measure by averaging the monthly series.

[22] Let $u_t = A\epsilon_t$, where $\epsilon_t \sim N(0_n, I_n)$ is a $n \times 1$ vector of structural disturbances and A is such that $AA' = \Sigma$. In order to identify all the shocks in the system we need at least $n(n-1)/2$ additional restrictions. The additional (sign) restrictions are imposed using the QR decomposition algorithm proposed by Rubio-Ramirez, Waggoner and Zha (2010): 1. Make a draw from a $MN(0_n, I_n)$ and perform a QR decomposition of the matrix with the diagonal of R normalized to be positive, where $QQ' = I_n$. 2. Assume that S is the lower triangular Cholesky decomposition of Σ (in principle any different decomposition such that $SS' = \Sigma$ will do the work). Compute the candidate impulse responses $IRF_j = C_j SQ'$, where C_j are the reduced form impulse responses, for $j = 0, \ldots, J$. If all the IRFs satisfy the sign restrictions, store them. If not, discard them and go back to the first step. 3. Repeat steps 1 and 2 until M impulse responses are obtained (say, $M = 1000$ times).

[23] For more details see L. Krippner Shadow short rate (SSR).

Table 1: Sign Restrictions

	Supply	Demand	Monetary Policy
GDP	+	+	/
GDPDEF	-	+	/
SSR	/	/	-
Spread	+	+	-
Share Price	+	+	+

Note: The table lists signs of reactions of endogenous variables (in the first columns) to a positive demand shock, a positive supply shock, and a negative monetary policy shock, respectively. Restrictions are imposed on impact and one period ahead.

expansionary monetary policy; we also consider the spread between the long and short-term rate (10 years government bond - 3 months rate) and the share price index for Italy. All variables are in growth rates except for the SSR and the spread, which are in basis points. In particular, we are interested in identifying a monetary policy shock by assuming that monetary expansion leads to an increase in output and prices and to a decrease in the spread. Responses are comparable to the baseline results (see Figure 16 in Appendix B), although the increase is weaker while share prices increase on impact and then drop quickly over the entire horizon.

5 The Effects of Monetary Policy Shocks on Inequality

To gauge the effects of conventional and unconventional monetary shocks on income inequality and distribution, we adopt the same econometric technique described in section 2. However, Gini coefficients and other inequality measures are sampled annually, while macroeconomic and financial variables are sampled quarterly. If, on the one hand, the annual frequency is more suitable to capture the effect on income distribution given the slow movements of the dispersion measures over a single quarter or even more a single month, on the other hand, it could be a limit for the analyses of monetary policies on inequality due to the less efficient estimate based on such an extraordinary short sample. To address this mixed-frequency problem we follow an approach of temporal disaggregation adopting the Chow-Lin regression models in Quilis (2013) which allows us to transform low-frequency data (e.g., annual data) into high-frequency data (e.g., quarterly data)[24]. In particular, we have used quarterly data for GDP and inflation as indicators and used it to interpolate all inequality measures. For each series of inequality measures, we end up with a longer time span from 1999q1 to 2017q4. Subsequently, we apply the local projection, and estimate a version of equation (3) using inequality measures and monetary surprises on a quarterly basis:

$$Z_{i,t+h} = \alpha_i^{(h)} + \Sigma_{j=1}^{J} \rho_{i,j}^{(h)} X_{i,t-j} + \beta_i^{(h)} \epsilon_t^{MP,q} + \eta_{i,t+h} \qquad h = 0, ..., H \tag{4}$$

where Z_i corresponds, alternatively, to:

- The Gini index
- The difference of log-levels between the 90th and the 10th percentile and the 75th and the 25th percentile
- The (log) cross-sectional standard deviation is also computed to conduct a robustness check
- and finally, the percentiles, expressed in logarithms, of the distribution P10, P25, P50, P75, P90, and P99.

Like the cross-sectional standard deviation, the use of logs requires the elimination of observations with values of zero. However, taking logs allows us to diminish the sensitivity to outliers. In fact, the advantage of the percentile differential in log levels is that they are less sensitive to extreme observations in the tails of the distributions. Following Coibion et al. (2017), we construct each measure of inequality based on disposable income, disposable income before transfers, as well as labour income, financial capital income, and financial

[24]For technical details on temporal disaggregation methods see the Eurostat guidelines on temporal disaggregation, benchmarking and reconciliation Buono et al. (2018).

wealth. The specification in (4) allows for a contemporaneous effect of the unconventional monetary policy shock on the inequality measure of interest[25]. At the same time, we add some additional controls in X including the same set of control variables as in (3) distinguishing between conventional and unconventional scenarios (including, among others, the excess bond premium and the spread respectively). All control variables are macroeconomic forces that drive inequality measures. As a benchmark, we set $J = 4$.

First, we trace out the effect of an expansionary conventional monetary policy on inequality as a counterfactual scenario. In this setup, the purged monetary policy surprise we use in equation (3) is:

$$\epsilon_t^{MP,q} = [OIS1M]$$

Then, as in 4, we compare it with the effect of an expansionary unconventional monetary policy on inequality again using the whole sample 1999q1-2017q4. The monetary surprise purged from other anticipatory effects, we adopt in this version of the model (3) is the following:

$$\epsilon_t^{MP,q} = [OIS10Y]$$

We assess the effect on inequality using purged OIS6M and OIS2Y (named Timing and FG, respectively) as well, but the estimates are less statistically significant both at 1 and 1.65 confidence levels.

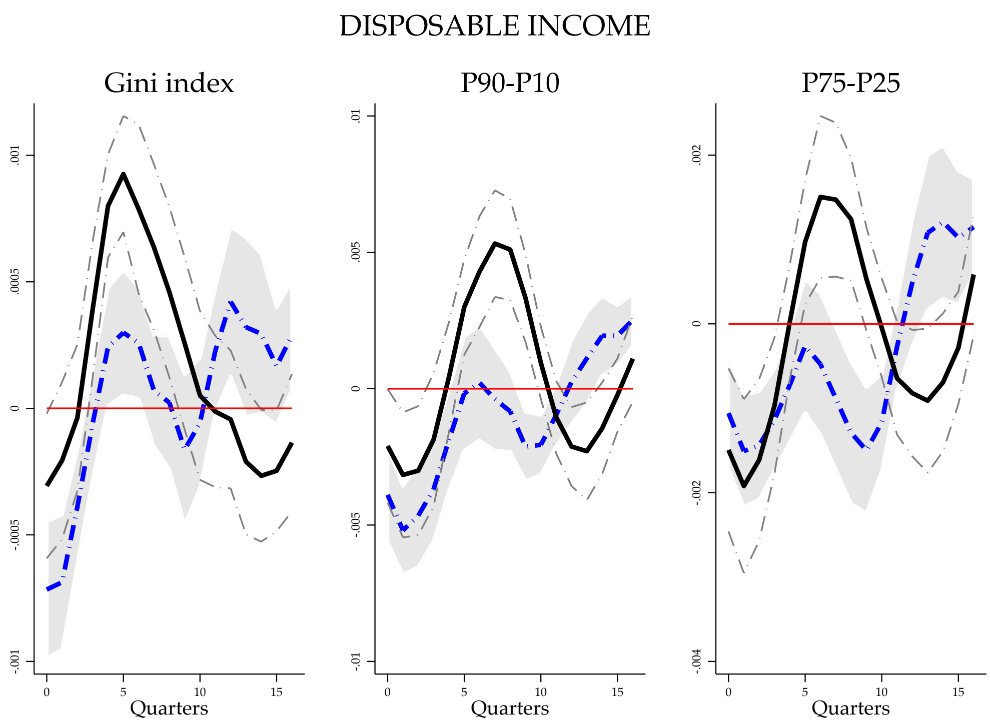
Impulse responses $\beta_i^{(h)}$, for $h = 0 \ldots 16$, are presented in the next section with 1 and 1.65 standard deviation confidence bands, computed with Newey-West heteroskedasticity and autocorrelation robust standard errors, as, except for h = 0, the errors are serially correlated.

[25]Furthermore, it is particularly convenient given the small sample at hand and its robustness towards misspecification.

5.1 Main Results

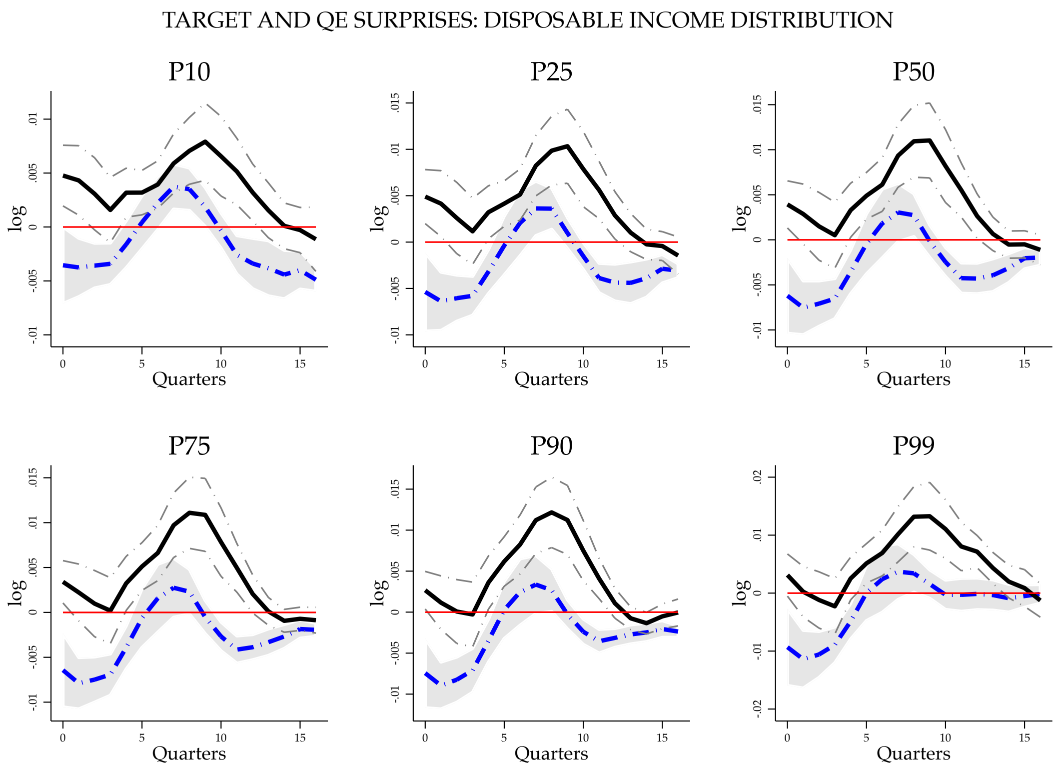
Figure 4 shows the effect of monetary surprises between the two scenarios conventional and unconventional, respectively: the effect of an expansionary monetary policy on total disposable income reduces inequality in Italy both in standard and non-standard times but, while in the first scenario, the effect is more evident and persistent, the impact of QE is unequalizing on impact but immediately reverts after one period when the Gini index shows an upward trend reaching a peak between the sixth and seventh quarters. It exhibits a marked reduction only in the long run. Overall, the size of the equalizing effect is modest for both conventional and unconventional scenarios.

Figure 4: IRFs of Conventional (blue dash-dotted line) and Unconventional (black line) Monetary Policy on Disposable Income Inequality Measures



Note: Impulse responses of the Gini index (percentage points), P90-P10, and P75-P25 (difference of log-levels) to a 100 bp. expansionary monetary policy shock. The dash-dotted grey lines and light-shaded areas are both 68% confidence bands.

Figure 5: IRFs of Disposable Income Percentiles



Note: Impulse responses of income percentiles in log levels to a 100 bp. expansionary monetary policy shocks both unconventional (black solid line) and conventional (blue dash-dot line). The dotted line and light-shaded areas are 68% confidence bands.

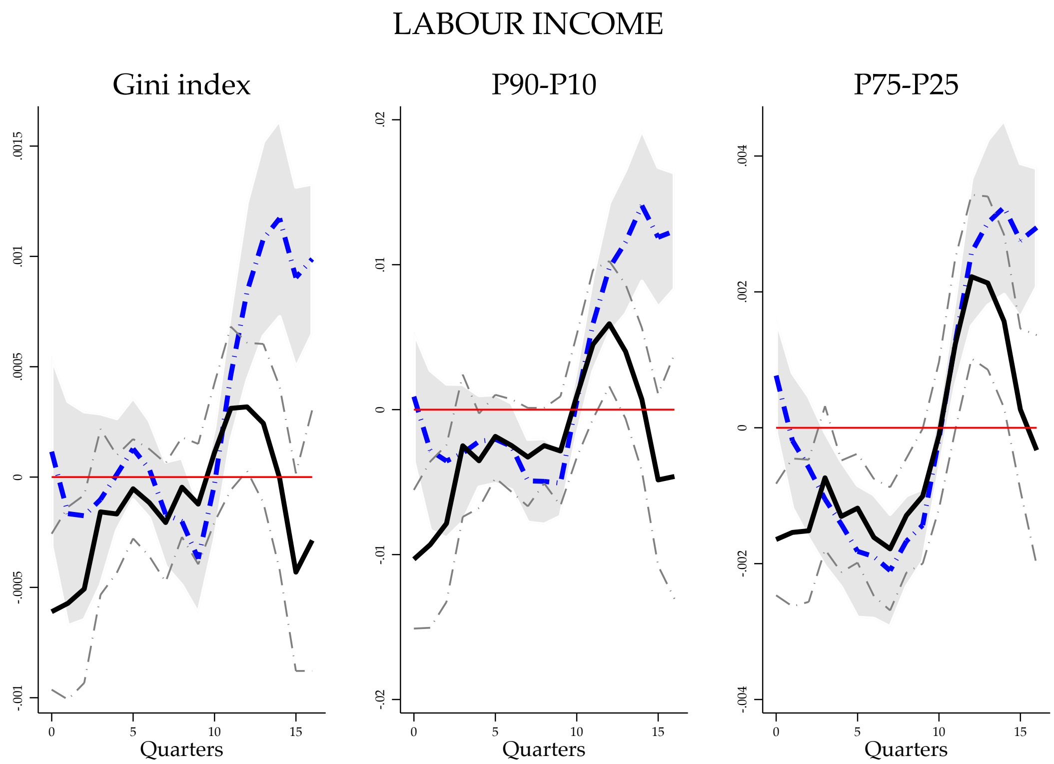
A plausible explanation of the different behaviour of the inequality measures between conventional and unconventional depends on the term structure of the policy rates that are at play. In the case of conventional monetary policy, a decrease in the short-term interest rate favours mainly constrained households by reducing interest rates on mortgages and loans. The credit channel improves savings and consequently reduces inequality in the short run. On the contrary, the long-term rate that is mainly at play in the unconventional scenario, reduces the rate of spread and the public bond rate, worsening the households' savings. In the short and medium run, the general improvement of economic conditions and the persistent increase in employment and wages help to reduce inequality. Since policy rates have been unusually low for a long time, this result might suggest more persistent distributional effects than during a normal interest rate cycle (Domanski et al. (2016)).

Looking at the income distribution (Figure 5), on impact, the QE shock favours the bottom of the distribution more than the conventional case. The sign of the responses is positive and the same for each percentile. However, lower percentiles (the 10th and 25th) appear to be the ones that benefit the most from the unconventional policy showing persistent increasing dynamics, while the responses appear less significant for the upper percentiles (the 90th and 99th) for which an increase is observed after the first year.

The effect of the unconventional monetary policy is also equalizing for labour income. As illustrated in Figure 6, the size and dynamics of labour income inequality indicators are consistently equalizing across the horizon. The effect of conventional monetary shock is less equalizing. In the latter case, the positive effects on inequality derived by expanding employment and wages are not so meaningful in affecting positively inequality as is the case with non-standard monetary policy.

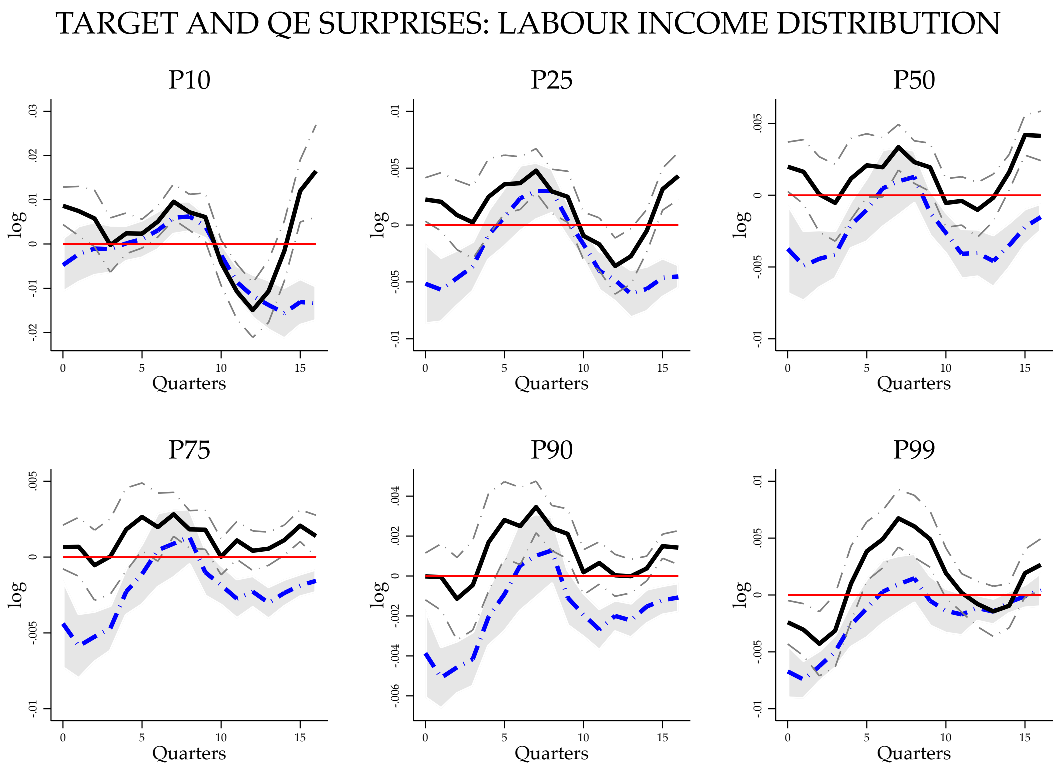
Looking at the labour income percentiles, the bottom of the distribution, in particular those of the 10th and 25th, are the ones that benefit the most from the unconventional policy after one year, probably reflecting the slow recovery of employment in Italy after the financial crises (Figure 7). Additionally, we can assess the QE effect on employee and self-employment

Figure 6: IRFs of Conventional (blue dashed-dotted line) and Unconventional (black line) Monetary Policy on Labour Income Inequality Measures



Note: Impulse responses of the Gini index (percentage points), P90-P10, and P75-P25 (difference of log levels) to a 100 bp. expansionary monetary policy shock. The grey dash-dotted lines and light-shaded areas are 68% confidence bands.

Figure 7: IRFs of Labour Income Percentiles



Note: Impulse responses of income percentiles in log levels to a 100 bp. expansionary monetary policy shocks both unconventional (black solid line) and conventional (blue dash-dot line). The dotted line and light-shaded areas are 68% confidence bands.

Figure 8: IRFs of Unconventional Monetary Policy on Employee and Self-Employment Inequality

Note: Impulse responses of employee and self-employment the Gini index to a 100 bp. expansionary monetary policy shock. The dark- and light-shaded areas are 68% and 90% confidence bands, respectively.

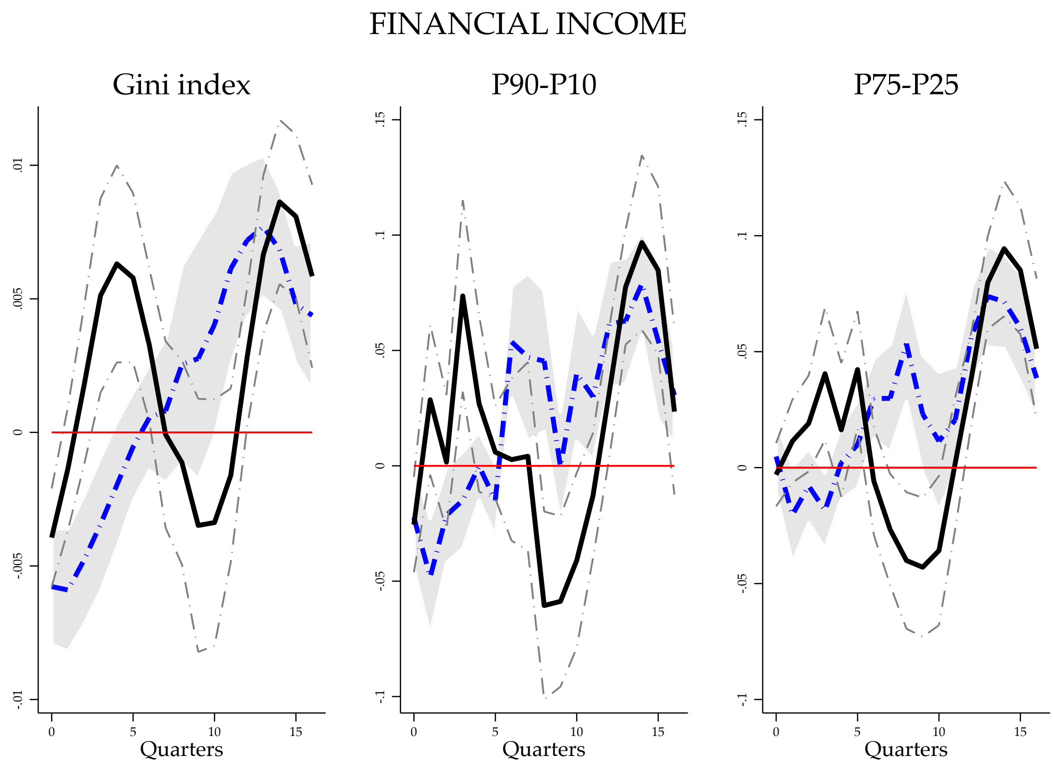
income and gauge in some way the earnings heterogeneity channel. Figure 8 compares the responses of the monetary surprises related only to the QE shock: the Gini index calculated on employee incomes decreases immediately and persistently after the shock, while the effect on self-employment is slightly equalizing in the short run and then turns to be unequalizing afterwards with a peak at the end of the third year. In fact, the IRFs do not fully reflect the recent recovery of self-employment labour income in Italy.

On the other hand, financial income inequality shows a more volatile behaviour: while in the conventional case, the Gini coefficient decreases in the short run, in the unconventional case, the Gini coefficient decreases on impact and then increases persistently from the first quarter up to the eighth, then decreases again showing up and down dynamics, giving back an ambiguous effect (Figure 9).

The rapid decrease in the middle and top percentiles is primarily responsible for increasing inequality over the distribution, with the former showing a larger magnitude over the horizon. The responses appear largely volatile for the 75th, 90th, and 99th percentiles, for which, if anything, the decline of income is observed for a long period (Figure 10). These outcomes could reflect different household behaviours: those who gained low financial incomes switched rapidly toward more profitable assets, such as mutual funds (a widespread asset in Italy after the financial crises: from 2008 to 2016, they increased by about 5 points. See Household Financial Assets, OECD). Over the unconventional scenario, stock prices in Italy appear to have reacted less than in the United States and the United Kingdom, resulting in households at the top of the financial income distribution keeping their portfolio unchanged for a longer period and benefiting less from higher asset values. All in all, both labour and financial incomes have contributed to lower inequality in disposable income, confirming that the income composition channel has been activated during the QE period.

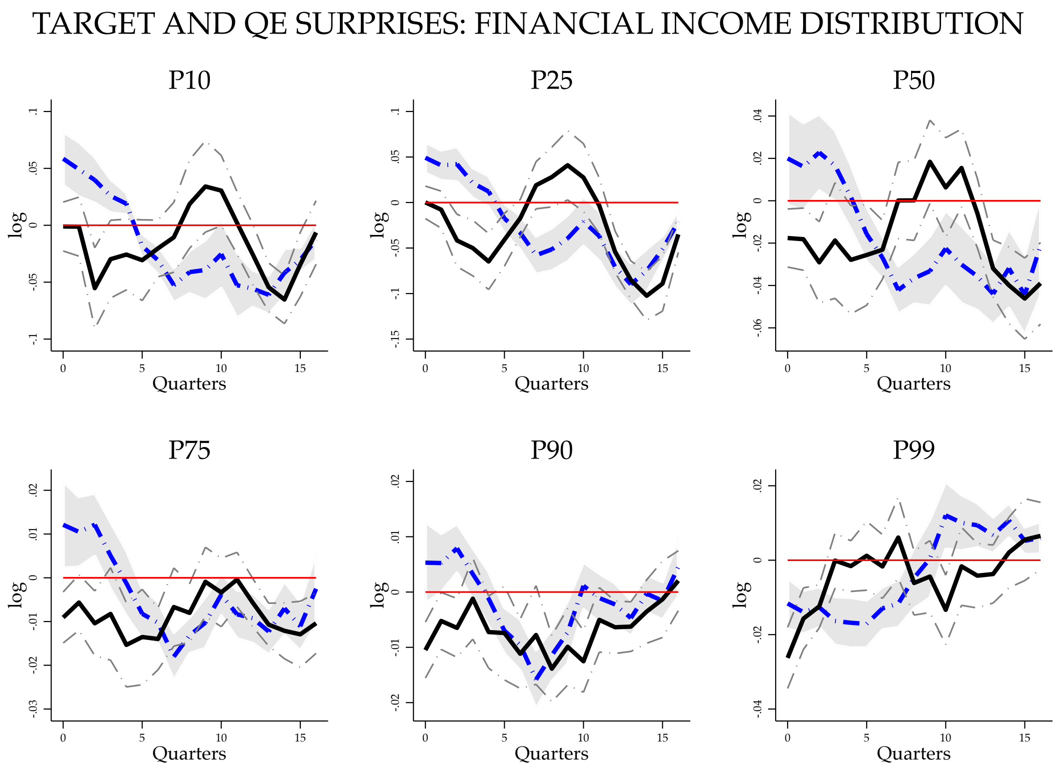
The responses of financial wealth and the financial wealth distribution are presented in Figures 11 and 12, respectively. Both in the conventional and unconventional cases, the inequality measures reduce on impact, showing fluctuating dynamics over the horizon.

Figure 9: IRFs of Conventional (blue dashed-dotted line) and Unconventional (black line) Monetary Policy on Financial Income Inequality Measures



Note: Impulse responses of the Gini index (percentage points), P90-P10, and P75-P25 (difference of log levels) to a 100 bp. expansionary monetary policy shock. The dash-dotted lines and light-shaded areas are both 68% confidence bands.

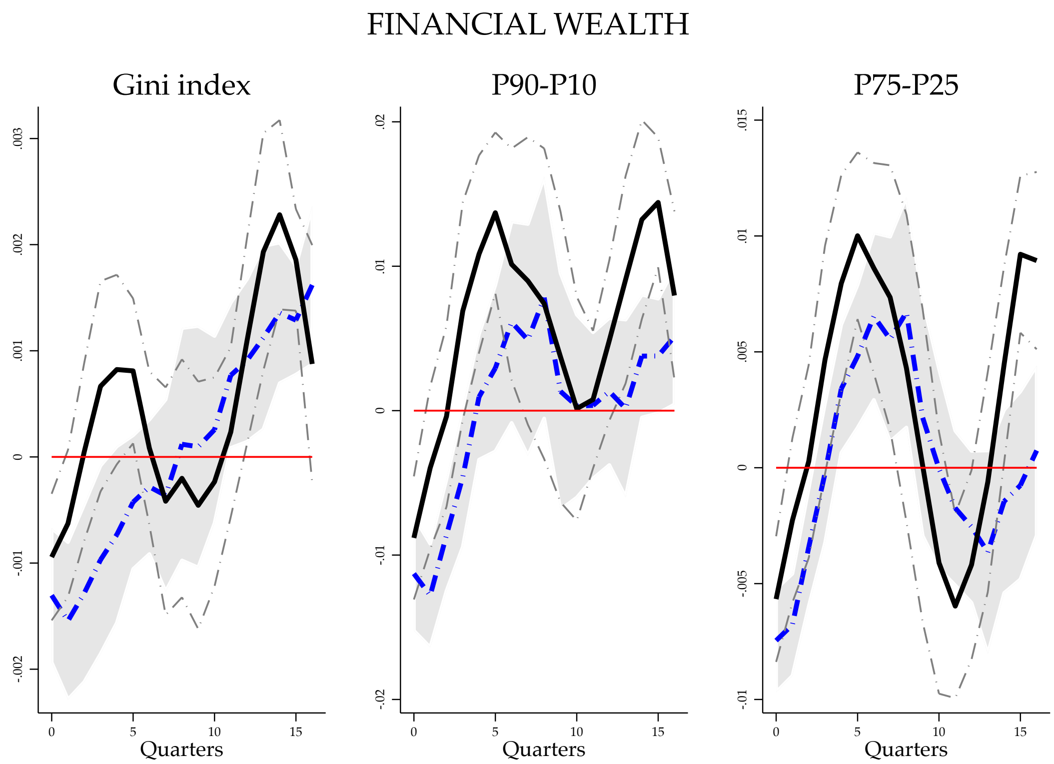
Figure 10: IRFs of Financial Income Percentiles



Note: Impulse responses of income percentiles in log levels to a 100 bp. expansionary monetary policy shocks both unconventional (black solid line) and conventional (blue dash-dot line). The dotted line and light-shaded areas are 68% confidence bands.

The impulse responses of the other measures of financial wealth inequality exhibit similar dynamics, returning an ambiguous effect on average.

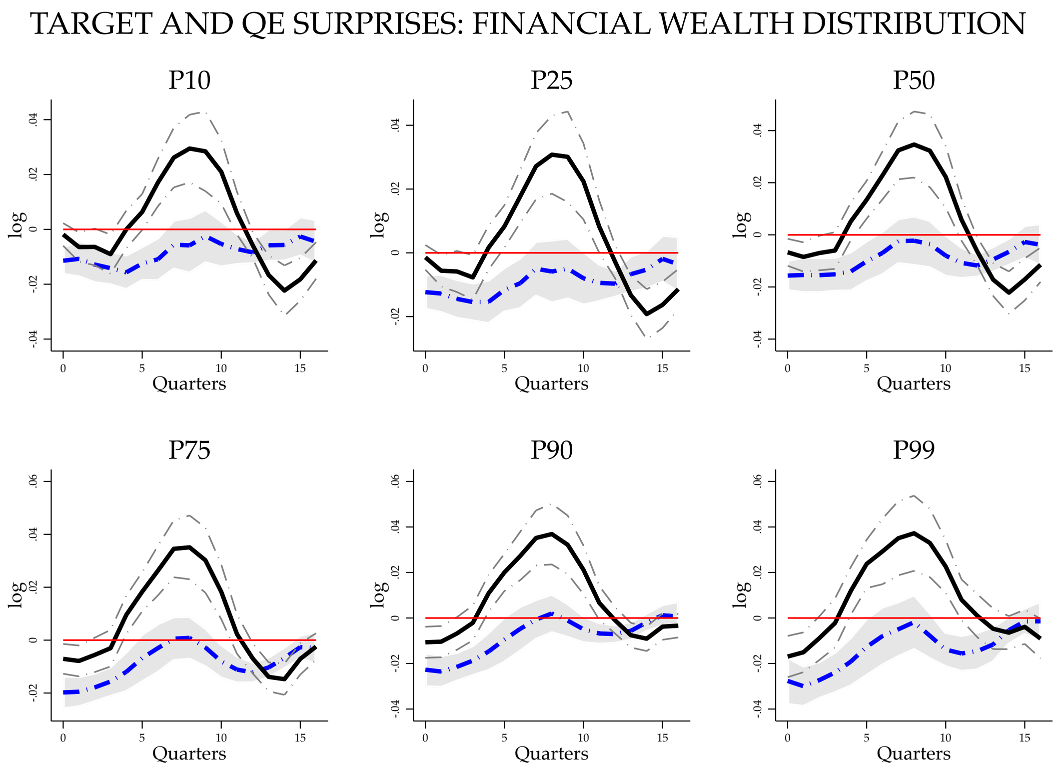
Figure 11: IRFs of Conventional (blue dash-dotted line) and Unconventional (black line) Monetary Policy on Financial Wealth Inequality Measures



Note: Impulse responses of Gini index (percentage points), P90-P10, and P75-P25 (difference of log levels) to a 100 bp. expansionary monetary policy shock. The grey dash-dotted lines and light-shaded areas are 68% confidence bands.

Diversely from the financial income distribution, this dynamic is mainly driven by the sharp and large rise in the top of the distribution, 75th, 90th, and 99th percentiles, with a pick in the second year. The top 1% reaches the highest benefits after eight quarters. Afterwards, the IRFs related to these percentiles exhibit a sharp downturn. Furthermore, the less negative reaction of the bottom of the distribution up to the 50th percentile is not long-lived. The heterogeneous responses across percentiles could explain the puzzling behaviour of the financial wealth inequality measures after a QE shock. The behaviour of

Figure 12: IRFs of Financial Wealth Percentiles



Note: Impulse responses of income percentiles in log levels to a 100 bp. expansionary monetary policy shocks both unconventional (black solid line) and conventional (blue dash-dot line). The dotted line and light-shaded areas are 68% confidence bands.

the wealth distribution is completely different in the conventional case: a 100 basis points decrease in the policy surprise, lowered all the percentiles meaning that the standard monetary policy works differently as it affects all families that hold securities and deposits. Taking into account that risky financial assets are almost exclusively held by the upper deciles of the gross wealth distribution, the financial segmentation channel seems to be activated under the non-standard monetary policy in favour of median and wealthy households with a peak in the second year and a sharp decline afterwards. Only in the medium term, the decline of the Gini index reflects some gains for the bottom of the distribution.

5.2 Effects on Subgroups of Households and Other Possible Extensions

As a further extension, we consider some specific questions raised in the public debate. One is whether non-standard measures differ from conventional monetary policies in the extent to which they may cause an "expropriation of savers" (Casiraghi et al. (2018)): monetary expansion makes borrowers better off by reducing the interest payments on debt (i.e, housing mortgages), while savers holding deposits and securities face lower returns.

Following Guerello (2017), another concern is the redistributive role of fiscal policy after the global financial crises since low-income households tend to rely more on transfers while middle-income households rely on labour income and those at the upper tail of the income distribution will rely relatively more on business and capital income (Colciago et al. (2019)). Consequently, we analyze the impact of QE on household disposable income before and after transfers.

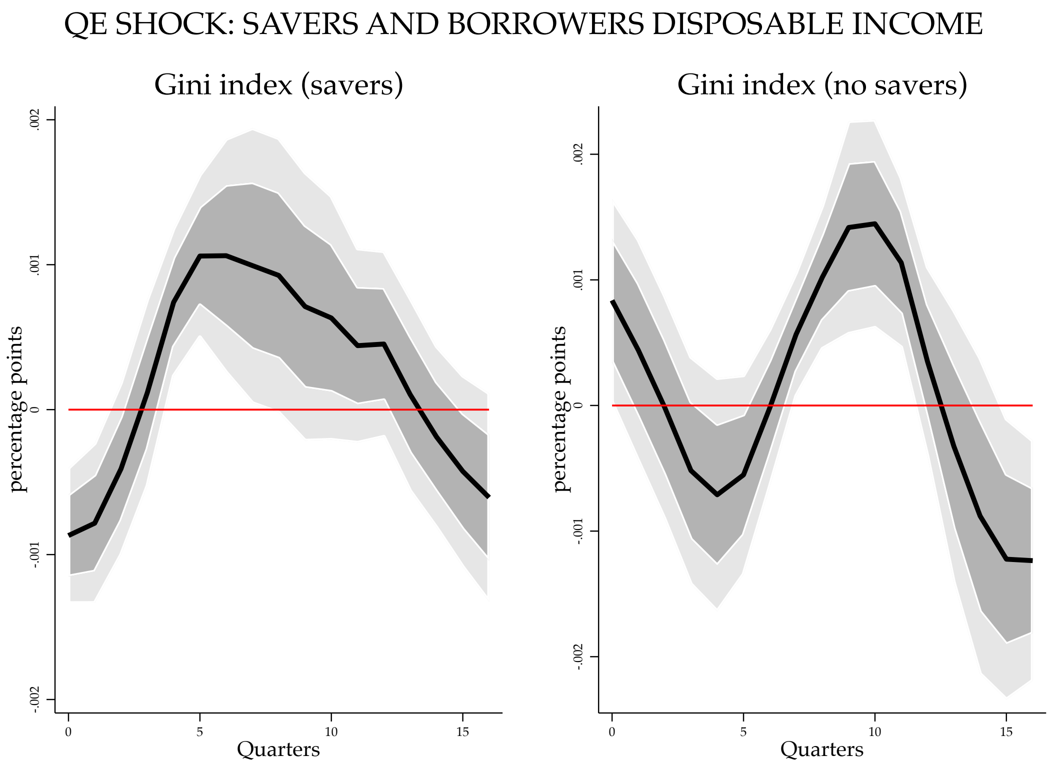
At the end of 2017 in Italy, housing was the main investment for Italian households and represented half of the gross wealth with a value of 5.246 billion euros although, since 2011, the ratio of dwellings to total assets declined in the following years, falling from 54 to 49 percent in 2017. Furthermore, the downward trend in the prices of residential housing in Italy, underway since 2012, has resulted in a reduction in the average value of housing and the ensuing contraction in the value of housing wealth (BdI-Istat Report, 2019). According to the Istat Household Budget Survey, in the same year, mortgagors represented 19.6% of households living in their dwellings (13.4% in 2008). Furthermore, with respect to financial capital, the share of deposits in the Italian financial portfolio increased slightly from about 10 to 13 per cent between 2005 and 2017, while the share of securities strongly declined from about 8 to 3 per cent in the same period and the shares and other equity fell from 12 to 9.7 per cent (BdI-Istat Report, 2019).

The EU-SILC survey makes available some information on households' savings and housing tenure status (that is, owners, and mortgagors). Thus, we can analyze the impact of non-standard monetary policy on the so-called "savers" households, defined as families with capital income (real and financial)[26] and without a mortgage, and on the "borrowers" households, defined as families without capital income but with a mortgage assessing whether the saving redistribution channel worked. According to Cloyne et al. (2018), housing tenure is a useful proxy for the balance sheet positions of households. Mortgagors, by definition, have sizable debt but also sizable wealth (which is typically tied up in their house), while outright owners have sizable housing and other financial wealth.

As shown in Figure 13 non-standard monetary policy, namely QE, is equalizing for savers in the short run. From the third period ahead, the IRF shows an upturn in dynamics, probably because incomes from real and financial capital are eroded sharply from low-interest rates, as in a standard monetary policy. Even if on a lower magnitude, the impact for borrowers is not equalizing on impact, meaning that the prolonged period of low-interest rates allows people to get access to cheaper loans, taking a larger advantage, due to their higher leverage only in the short run. The Italians are notable savers. Despite their conservative financial habits, after the global financial crisis of 2008, they were forced to consider investments other than government bonds and deposits. Therefore, savers appear to have been hit hard by non-standard monetary policies only in the medium run.

[26] According to the EU-SILC definition, capital incomes include property rentals and capital gains

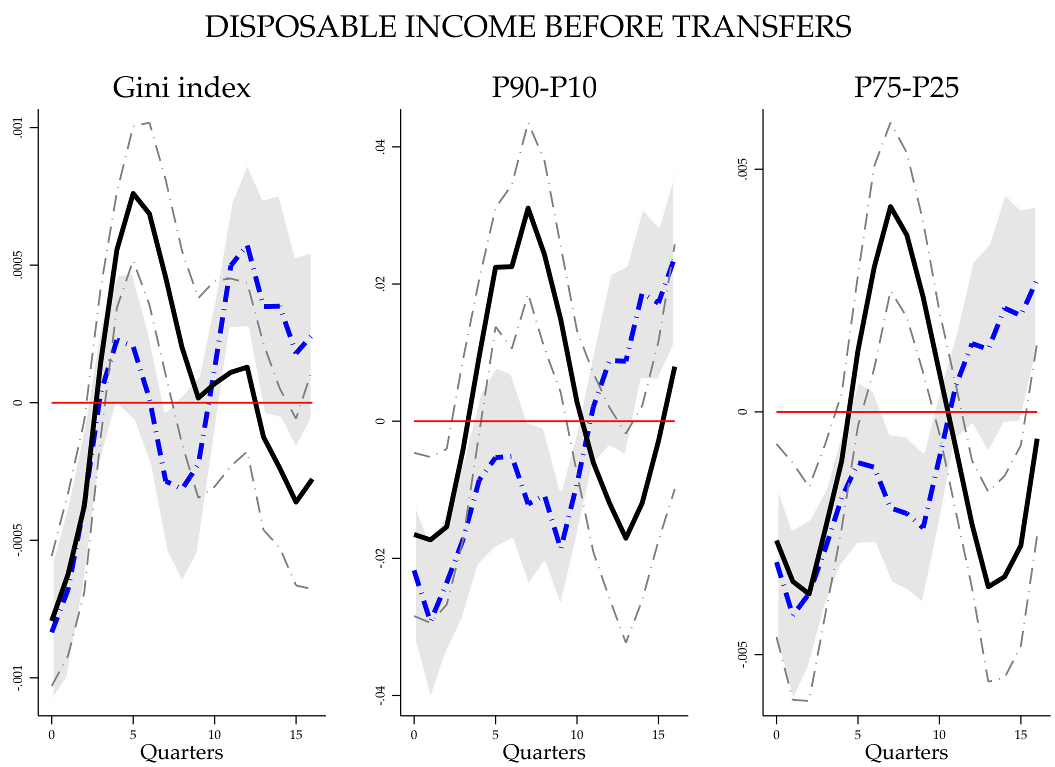
Figure 13: IRFs of Unconventional Monetary Policy on Savers and Non-Savers Disposable Income Inequality



Note: Impulse responses of savers and non-savers the Gini index to a 100 bp. expansionary monetary policy shock. The dark- and light-shaded areas are 68% and 90% confidence bands, respectively.

Turning our attention to the second issue, we find that redistributive policies might not have affected the distribution of income and its response to external shocks given the limited role played by fiscal policy in Italy in recent years due to fiscal compact rules adopted by euro area countries after the sovereign debt crisis. Following Guerello (2017), the comparison of the Gini index of disposable income before and after social transfers (pension excluded) provided by the EU-SILC database can be considered as a proxy of the redistributional fiscal policy effects.[27]

Figure 14: IRFs of Conventional (blue dash-dotted line) and Unconventional (black line) Monetary Policy on Disposable Income Inequality Measures



Note: Impulse responses of the Gini index (percentage points), P90-P10, and P75-P25 (difference of log levels) to a 100 bp. expansionary monetary policy shock. The grey dash-dotted lines and light-shaded areas are 68% confidence bands.

Figure 14 shows that the effect of an expansionary monetary policy on disposable income

[27] We do not use a pre-tax income as from 2007 to 2017 there were no significant changes in tax rates or tax brackets in Italy.

before transfers reduces inequality in Italy both in standard and non-standard times only in the first period. The size of the effects is larger than for disposable income after transfers, meaning that low-income households have benefited more from the effect of monetary policy other than fiscal transfers over the horizon if anything. A plausible explanation is that following the sovereign debt crises, tightening fiscal rules has limited government policy actions in Italy and other European countries. For these reasons, the social tensions associated with fiscal consolidation, in part stemming from the global financial crisis, have put the distributional impact of government tax and spending policies at the heart of the public debate in many countries. According to Bernanke (2015), it would be preferable to have more proactive fiscal policies and a more balanced monetary-fiscal mix when interest rates are close to zero.

5.2.1 Other Robustness

We also conduct a robustness check analysis by adopting the same methodology with another measure of inequality for each scenario we have discussed above: the cross-sectional standard deviation of log levels, which reduces the sensitivity to extreme values of the distribution by removing zero values. Figure 17 in Appendix B shows the impulse response functions of disposable income, disposable income before transfers, labour income, financial capital income, and financial wealth in both conventional and unconventional monetary policy scenarios. The results are broadly consistent with what we found in the previous sections for both the short and the long-run dynamics.

Finally, we show the sensitivity of IRFs to different lag lengths by including in the LP model lags of monetary policy shocks and lags of the inequality measures to the first two. The results are not altered by these changes.

6 Conclusion

In this paper, we investigate the effects of conventional and unconventional monetary policy shocks on income inequality in Italy, exploiting for the first time the household survey microdata on Income and Living Conditions (EU-SILC, Istat) that allows us to compute inequality measures over time and for specific incomes and subgroups of individuals (savers vs. non-savers, employees vs. self-employment workers). To this aim, we focus mainly on the income composition channel and the financial channel.

The main results of the impact of a monetary policy shock on income distribution in Italy, show that the equalizing effect of the standard policy is more evident in comparison to the unconventional scenario, although the responses of the Gini coefficient are small in magnitude. In the non-standard scenario, the overall impact is driven by the sharp reduction of labour income inequality measures (in particular those of employees) due to an increase in GDP and employment. The response of financial income inequality measures exhibits ambiguous effects over the horizon. When we consider the response of disposable income before social transfers (pension excluded), we find an equalizing effect of higher magnitude in the unconventional scenario, meaning that fiscal policy did not have a crucial redistributive role in Italy during the crises and the recovery period. Turning our attention to the financial channel, the non-standard monetary policy shows at first glance an ambiguous effect favouring the median and wealthy households up to the second period. The top 1% gets the higher benefits. Subsequently, the prolonged decline in the index of financial wealth reflects some gains at the bottom of the distribution, meaning that unconventional monetary policy is no longer "neutral" over the cycle. Overall, the income composition channel works in the right direction during the QE period, even if the total impact on household incomes is modest and not prolonged.

Our results are less clear-cut than the recent work on income inequality in the euro area (see Lenza and Slacalek (2018) and Samarina and Nguyen (2019)) where the responses of the Gini coefficient to an expansionary monetary policy shock are also small in magnitude but statistically significant in the short run. Conversely, quite similar to the results in Casiraghi et al. (2018), savers appear not to have been "expropriated" during the QE period because they were partly compensated enough by the capital gains, while borrowers have benefited only in the medium run from their higher leverage due to lower interest rates. Hence, we can argue that converse to the US and UK, equity prices were not the main drivers of rising inequality in Italy.

In general, some evidence suggests that QE is associated with a decrease in inequality in Italian households by reducing mainly that of labour earnings in line with the euro area's experience, although its economic size is small. In this respect, other policies and economic forces could be responsible for the observed rise in income and wealth inequality in recent years holding important policy implications for government choices. Future research could investigate, for example, the key role of fiscal and redistributive policies and the extent to which the monetary-fiscal mix in Italy has been inadequate. Greater reliance on fiscal policy would probably give better results than changing the target for monetary policy.

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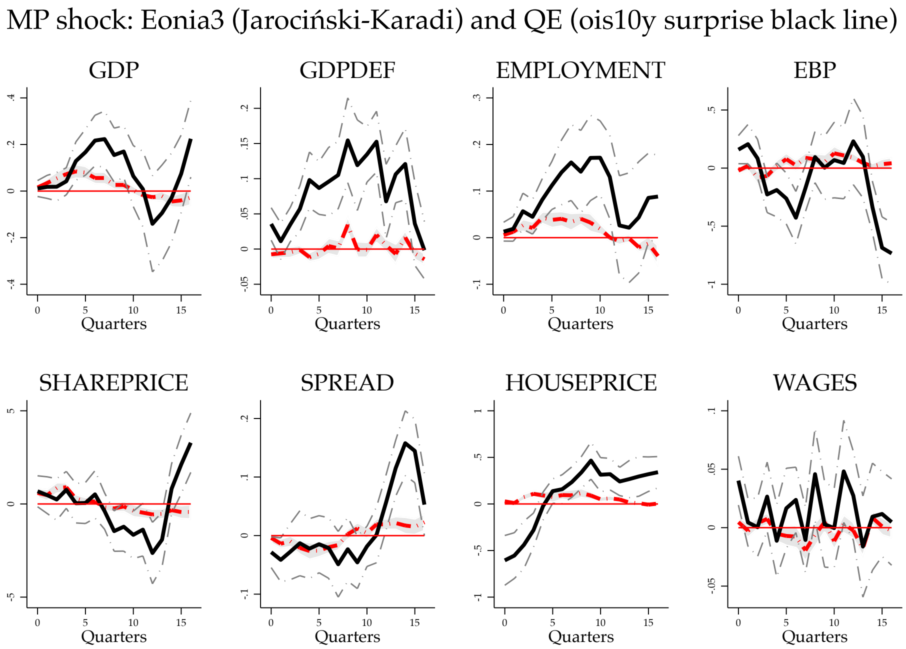
APPENDIX

A UNCONVENTIONAL MONETARY POLICY. ROBUSTNESS CHECK

A.1 IMPULSE RESPONSE FUNCTIONS COMPARING QE WITH JAROCINSKY AND KARADI MP SHOCKS

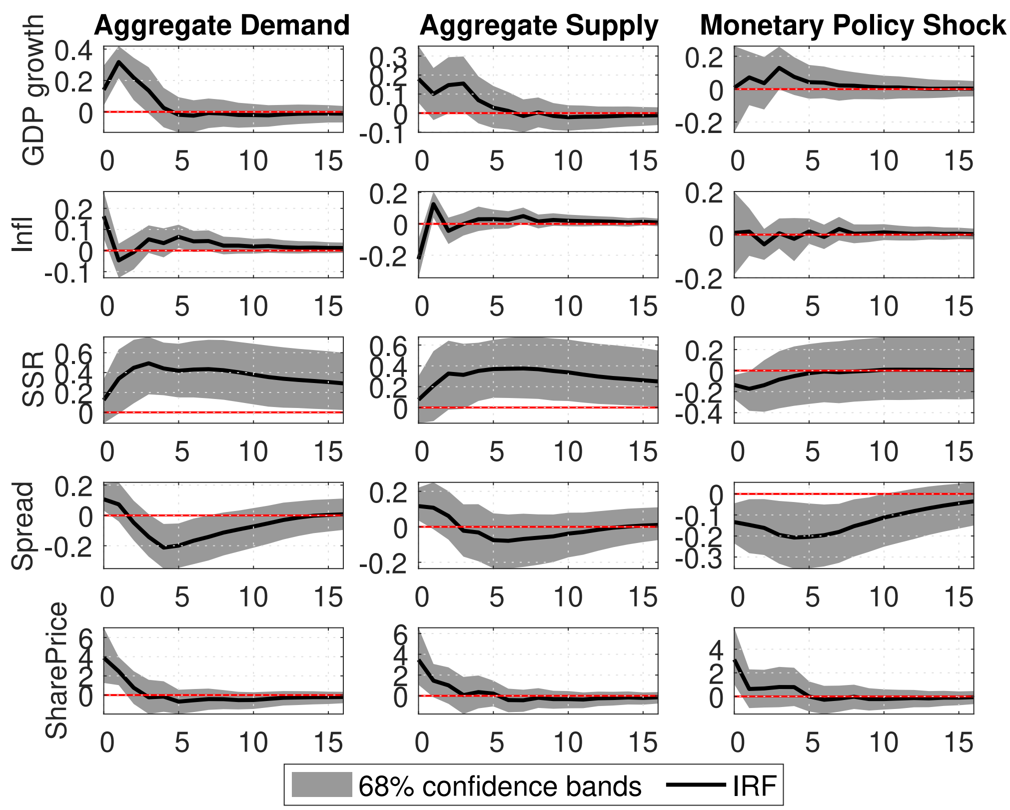
Figure 15: IRFs of QE and JK Monetary Policy Shocks



Note: Impulse responses of the different macroeconomic variables to a 100 bp. expansionary monetary policy comparing QE shock (solid black line) with the Jarocinsky-Karadi high-frequency monetary policy shocks (dashed red line) in the LP model over the sample 1999q1-2016q4 excluding the measure of interest $Z_{i,t}$ from the system. All the responses are in percentage points; IRFs of EBP and spread are in basis points. The dash-dotted grey lines and the light-shaded areas are 68% confidence bands.

A.2 IMPULSE RESPONSE FUNCTIONS USING THE SHADOW RATE BY L. KRIPPNER IN A SVAR WITH SIGN RESTRICTIONS

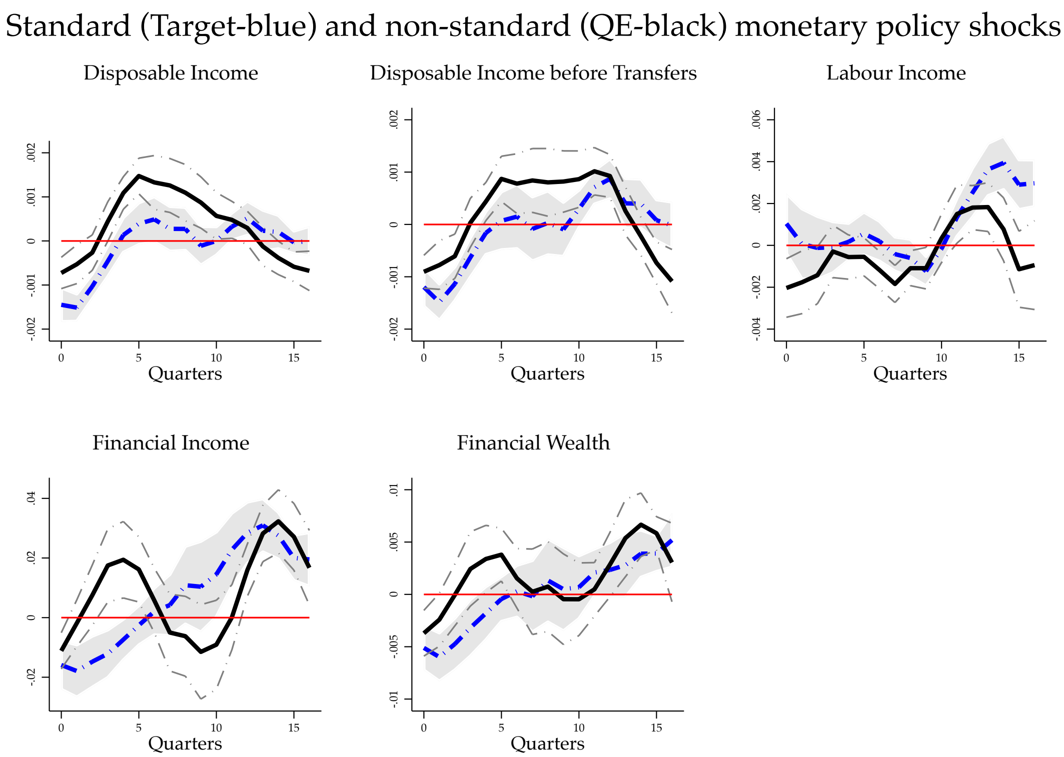
Figure 16: IRFs of an Expansionary Monetary Policy



Note: Impulse responses of the different macroeconomic variables to a 100 bp. expansionary monetary policy shock using the shadow short rate (SSR) in a SVAR model with sign restrictions excluding the measure of interest $Z_{i,t}$ from the system. All the responses are in percentage points; the spread is in basis points. The solid line is the point-wise median. The grey-shaded areas are 68% probability bands.

B EXPANSIONARY MONETARY POLICY SHOCKS ON INEQUALITY MEASURES IN ITALY. ROBUSTNESS CHECK

Figure 17: IRFs of Conventional (blue dash-dotted line) and Unconventional (black line) Monetary Policy on Log Cross-sectional Standard Deviation Measure of Different Incomes



Note: Impulse responses of Cross-sectional Sd to a 100 bp. expansionary monetary policy shock. The grey dash-dotted lines and light-shaded areas are 68% confidence bands.