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Income inequality, equities, household debt, and interest rates: Evidence from a century of data

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ABSTRACT

Using Philippon's (2015) recently published historical household debt data, this paper uses Diebold and Yilmaz's (2012) generalized variance decompositions and generalized impulse responses to understand the relationship between interest rates, the stock market, household debt, and the distribution of income in the U.S. The results indicate that increases in the stock market and household debt increase income inequality. Moreover, the relationship between the interest rate and income inequality is found to be negative and statistically significant. We interpret our results as suggesting that high income earners derive a larger portion of their income from interest rate sensitive assets.

1. Introduction

On October 17th, 2014, Federal Reserve Chairwoman Janet Yellen spent significant time discussing income inequality in the United States at a Boston Federal Reserve Conference on Economic Opportunity and Inequality. She stated:

> "……The extent of and continuing increase in inequality in the United States greatly concern me. The past several decades have seen the most sustained rise in inequality since the 19th century after more than 40 years of narrowing inequality following the Great Depression. By some estimates, income and wealth inequality are near their highest levels in the past hundred years, much higher than the average during that time span and probably higher than for much of American history before then. 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. I think it is appropriate to ask whether this trend is compatible with values rooted in our nation's history, among them the high value Americans have traditionally placed on equality of opportunity."[2]

Federal Reserve officials have often discussed income inequality in speeches, however, there is not a consensus regarding the degree to which income inequality should be a concern for the Federal Reserve. Chairman Alan Greenspan in 1998 stated:

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[1] This research was prepared by the author in his personal capacity. The opinions expressed in this article are the author's own and do not necessarily reflect the views of the United States Postal Service or the United States government.
[2] http://www.federalreserve.gov/newsevents/speech/yellen20141017 a.htm.

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"……..We need to ask, for example, whether we should be concerned with the degree of income inequality if all groups are experiencing relatively rapid gains in their real incomes, though those rates of gain may differ. And, we cannot ignore what is happening to the level of average income while looking at trends in the distribution. In this regard, our goal as central bankers should be clear: we must pursue monetary conditions in which stable prices contribute to maximizing sustainable long-run growth."[3]

Historically, the primary channel that the central bank could redistribute wealth was thought to be the inflation rate. Inflation that was higher than the expected inflation rate redistributed wealth from creditors to debtors. However, given that part of the Federal Reserve's mandate is a low unemployment rate, the Federal Reserve has often lowered interest rates in attempts to stimulate the economy. As such, while lowering interest rates may stimulate the economy, it is not clear that all income groups experience equal growth in incomes because of the policy stimulus. This paper explores whether there is a debt and equity channel through which changes in interest rates may affect income inequality through either increased household debt or by increasing the value of financial assets that are owned primarily by high income families.

Past studies have analyzed separately how these three variables (the interest rate, household debt, stock market) impact income inequality, but all four variables have not been analyzed simultaneously in a dynamic setting. Kumhof and Ranciere (2013) provide a theoretical framework linking income inequality and debt-to-income ratios. In their model, the key mechanism is that top earners use a substantial portion of their income to accumulate financial wealth through loans to those at the low-end of the income distribution.[4] Iacoviello (2008), using a DSGE model, shows that income inequality has primarily been increased by an expansion of credit from rich (saving) to poor (spending) households. Rajan (2010) and Reich (2010) provide qualitative arguments linking income inequality to debt levels. Coibion et al. (2012) examine the direct link between income inequality and the interest rate and they document four possible channels through which interest rates may affect inequality. First, households that own firms (i.e. equity holders) may do better during periods of monetary expansion if profits rise faster than wages.[5] Second and related to the first, households that are more integrated to financial markets, and thereby more integrated to central banks, may benefit more during monetary expansions as the price of credit falls. Third, the savings redistribution channel in which declines in inflation rates benefit savers. Lastly, they present the earnings heterogeneity channel in which wage income between low and high-income earners may differ as lower-income households are more likely to be unemployed if monetary contraction occurs and slows economic growth. They conclude that the financial segmentation channel and the portfolio channel will increase inequality when an expansionary monetary policy shock occurs. In contrast, the savings redistribution channel and earnings heterogeneity channels will decrease inequality after an expansionary monetary policy shock. Furceri et al. (2016) find that, for a panel of 32 advanced and emerging market countries over the period 1990–2013, expansionary monetary policy reduces income inequality (p. 20). However, they infer that monetary policy can increase inequality by boosting asset prices or inflation. Auclert (2016) also claims that low rates can increase asset prices, which then may exacerbate income inequality. It should be noted that declining interest rates may not be the result of any specific central bank policy. Slowing productivity growth in the U.S. or a global savings glut, as discussed by Bernanke (2010), may be the driving force behind low interest rates, especially since the 1980s.[6]

Our paper directly examines the response of equities and the response of aggregate household debt due to changes in interest rates using data beginning in 1919. We use data spanning from 1919 to 2009 which includes key historical periods, such as the Great Depression era and the 1950s and 1960s where inequality was quite low relative to the present. We show that low interest rates lead to increases in equity returns, increases in household indebtedness, and increases in income inequality. The reason we focus on testing for a household debt and equity channel is that debt and equities are significant components of households' balance sheets. As such, we provide further details on how these two components evolved differently over time among the households' balance sheets at different levels of the income distribution. Overall, we believe that our paper helps clarify the relationship between income inequality and interest rates by providing a more detailed examination of the debt and equity channels. To test our channels, we estimate impulse responses from both a structural vector autoregression (SVAR) and by using Koop et al. (1996) generalized impulse responses; the results show consistency across the two different specifications of the VARs. Additionally, we also estimate Diebold and Yilmaz's (2012) generalized variance decompositions. The rest of the paper proceeds as follows: section II discusses the composition of household wealth, section III discusses our data and methodology, section IV presents our results, and section V concludes.

2. Inequality and the sources of household income

Understanding the evolution of the different income groups and how they earn their income over time allows for a better understanding behind the purpose of our three different income inequality measures. It also highlights the significance of the

[3] http://www.federalreserve.gov/boarddocs/speeches/1998/19980828.htm.

[4] The reasons for increased household debt may be due to a "keeping up with the Jones'" story, but, barring surveys of *why* households are spending, it would be difficult to tell *why* they are increasing spending/consumption.

[5] Along these lines, Kaplan et al. (2016) shows that expansionary policy lowers the cost of funds for the financial sector, profits increase, and households then shift into illiquid productive assets (defined as corporate equity, private equity, and portions of housing and durable investment) (p. 42).

[6] https://www.federalreserve.gov/newsevents/speech/bernanke20100103 a.htm.

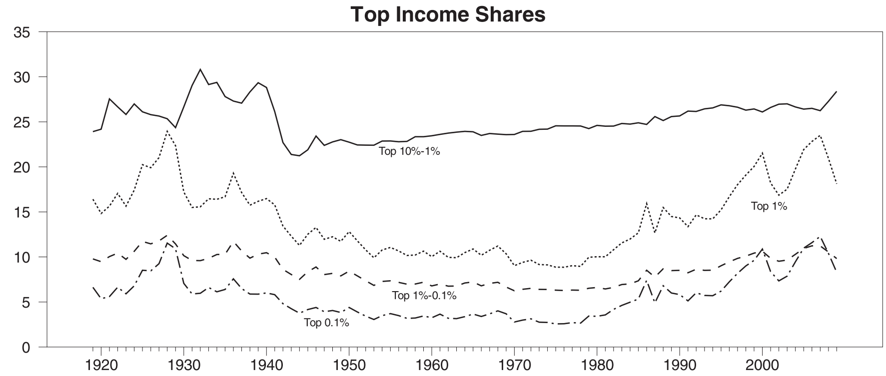

Fig. 1. Top income shares.

debt and equity channels through which monetary policy affects the distribution of income. Fig. 1 shows that the share of total income going to top income groups has increased dramatically, especially for the post-1980s period.

Interestingly, most of the changes in the top decile are due to large changes in the top centile. The "10% - 1%" income group captures the income share of the top decile, excluding the top 1%. Note that we do not see large changes in the income share of this group over time. The "10%-1%" share increased from 24.6% in 1980 to 26.2% in 2007. On the other hand, the income share of the top 1% increased from 10.0% to 23.5% over the same period. Within the top 1% group, it is the top 0.1% that has experienced the biggest increase in income. Their income share has almost quadrupled, from 3.4% in 1980 to 12.3% in 2007. Similarly, Saez and Zucman (2016) show, using data from the Survey of Consumer Finances, that the top 0.1% of households' incomes have increased dramatically since the 1970s. Also, Wolff (2012, 2014) explains that virtually all of the income gains since 1983 have gone to the top 20% of earners. It appears from our analysis, in correspondence with other authors, that the top 1%, particularly, experienced a large increase in income.[7]

We believe differences in the way households earn their income has contributed to increases in top income shares. Figs. 2–5 show the income sources for the top 0.1%, the top 1 %, and bottom 90% of income earners. For the bottom 90% group, most of their income comes from wages and very little income comes from capital gains, interest or dividends, or business equity. This has been consistent since 1989. On the other hand, more than 40% of income for the top 1% group and more than 50% of income for the top 0.1% group is from non-wage sources.[8]

Approximately, 15% of income for the top 1% group and almost 20% of income for the top 0.1% group comes from interest. For the bottom 90% group, this source of income is almost zero. Entrepreneurial activities provide 20% of income for the top 1% group and 30% of income for the top 0.1% group. However, for the bottom 90%, only 5% of income comes from entrepreneurial activities. From Fig. 5, we observe that realized capital gains are an important source of income for households at the top end of the income distribution; whereas, for the bottom 90%, this source of income is very close to zero. On average, realized capital gains compose 20% of income for the top 1% group and close to 40% for the top 0.1% group. A more detailed look into the breakdown of income in the past would be valuable but data pre-dating 1989 was not readily available for the bottom 90% group from the Survey of Consumer Finances.

Furthermore, Fig. 6 decomposes the balance sheet components of wealthy households and households in the middle 60% of the income distribution. As can be seen, for the top 1% group, 80% of wealth is held in business equities, financial instruments, and liquid assets. On the other hand, these three components represent less than 25% of wealth for the middle 60% of households. Roughly 2/3rds of the middle 60%'s wealth is in housing. Correspondingly, Doepke et al. (2015) assert that middle class households are generally highly leveraged, with many holding mortgage debts that are far larger than their net worth.

From Fig. 7, it can be seen that debt service, from the beginning of the 1990s, consistently increased until the end of 2007. This suggests that, over the last 20 years, households devoted larger shares of their income to paying interest or directly paying off their debt. The figure also shows that the increase in overall debt service was mainly driven by the increases in mortgage debt service. The debt service data are aggregated data and we cannot split them based on income quintiles; however, we can still say that most of the increase in debt service comes from households outside the top end of the income distribution. This is mainly because, for low to middle-income households, housing is their main source of wealth (as seen in Fig. 6). Furthermore, as shown in Fig. 8, only households in the top 10% of the income distribution have had their debt-to-assets ratio remain constant over the last 24 years. Whereas, for the other households, increases in leverage ranged from

[7] Heathcoate et al. (2010), in a micro-level study, also note that dispersion between the top (90th percentile) and middle incomes (50th percentile) has increased consistently since the 1970s (p. 23).

[8] Note the data source for the top 0.1% and top 1% is the World Wealth & Income Database and the income compositions are the share of total income excluding capital gains. The share of wages to total income would have been even lower for these two groups if capital gains were part of total income. The shares for the bottom 90% come from our own calculations using data from the Survey of Consumer Finances.

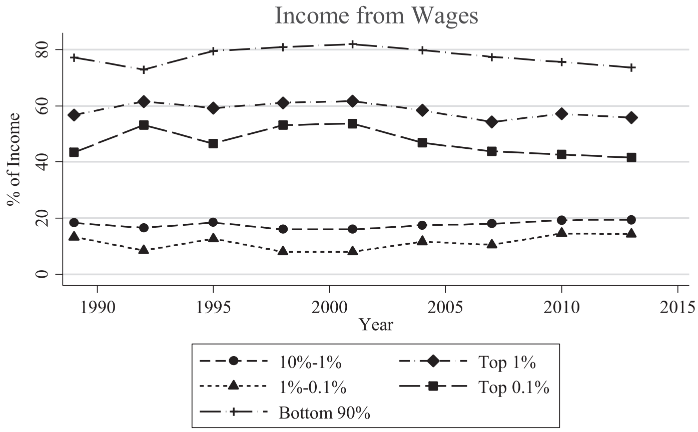

Fig. 2. Income shares from wages.

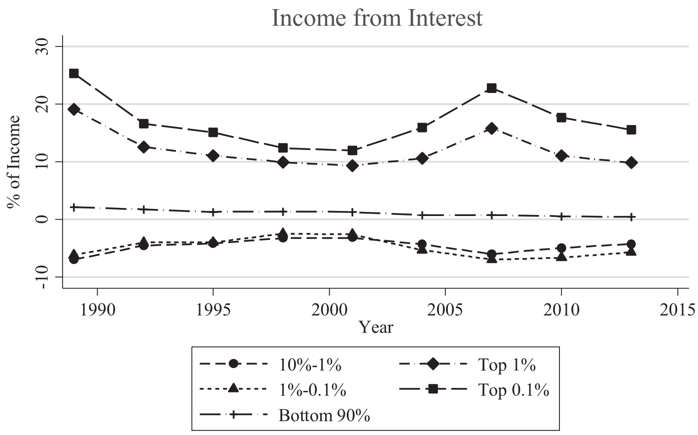

Fig. 3. Income shares from interest.

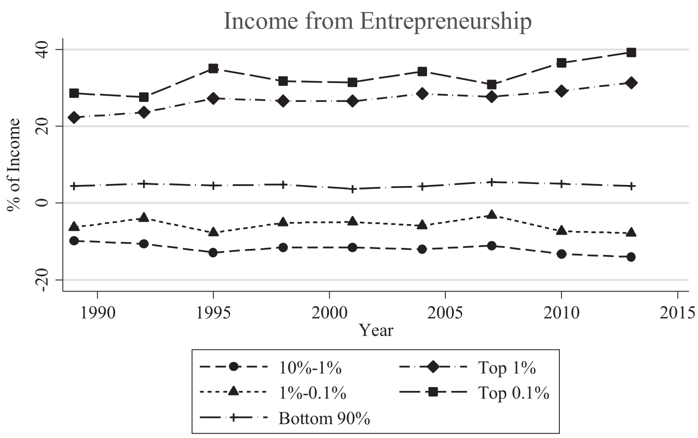

Fig. 4. Income shares from entreprenuership.

5% to nearly a 10% increase depending on the specific income groups. As such, increases in leverage mean increases in debt service.

The differences in how households earn their income is the mechanism through which we think changes in the interest rate, asset prices, and household debt are affecting the top earning households differently than lower income households.

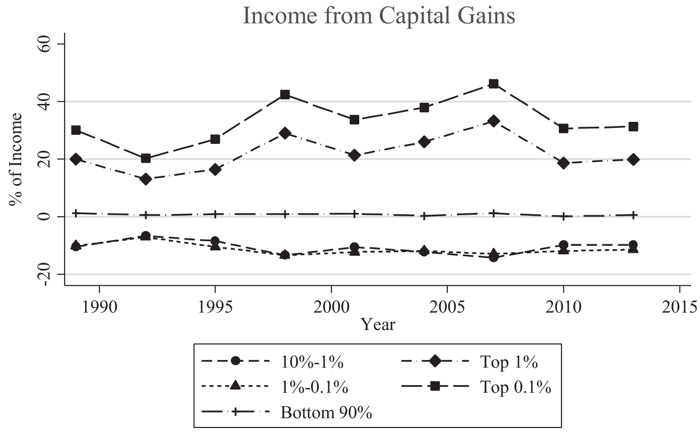

Fig. 5. Income shares from capital gains.

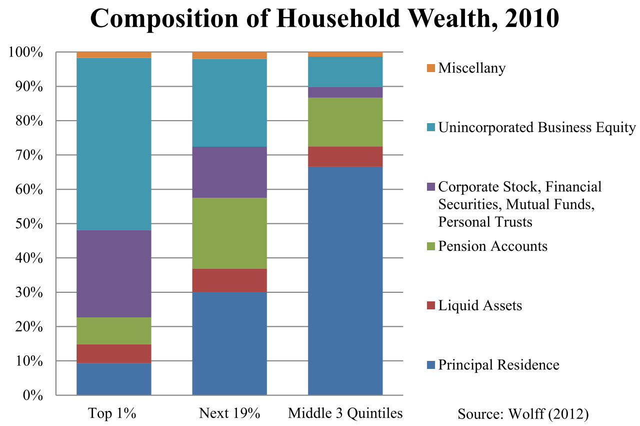

Fig. 6. Composition of household wealth.

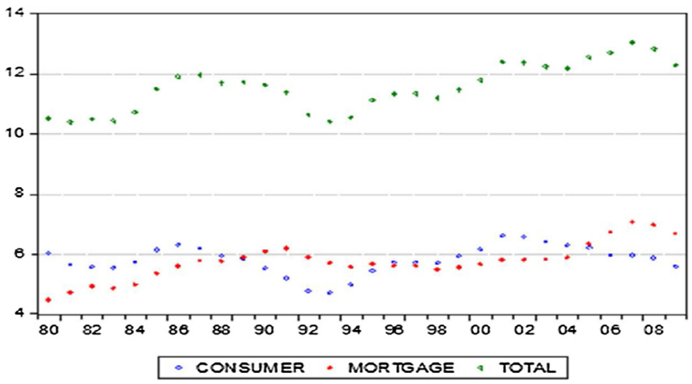

Fig. 7. Household debt as a ratio of income.

Specifically, the inverse link between the interest rate and equities, followed by increases in income inequality, we believe, is driven by the fact that the top income groups earn significantly more of their income and hold more of their wealth in equities. Owyang and Shell (2016) highlight that wealthy households own most of the equity in the United States and, thus, increases in the stock market disproportionately benefit high income families. Note in Fig. 9 that the top 10% of households have seen over a tripling in the real value of their financial assets; whereas, the bottom 90% of households have seen hardly any increase in the value of their assets. This most likely masks the true increase in financial assets of the top 1% and top 0.1%

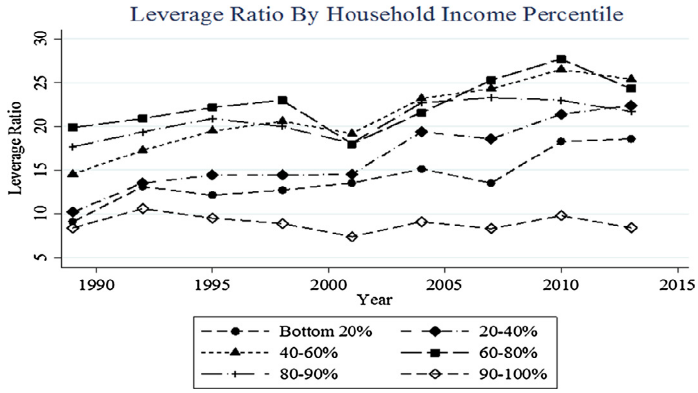

Fig. 8. Leverage ratio by household income percentile.

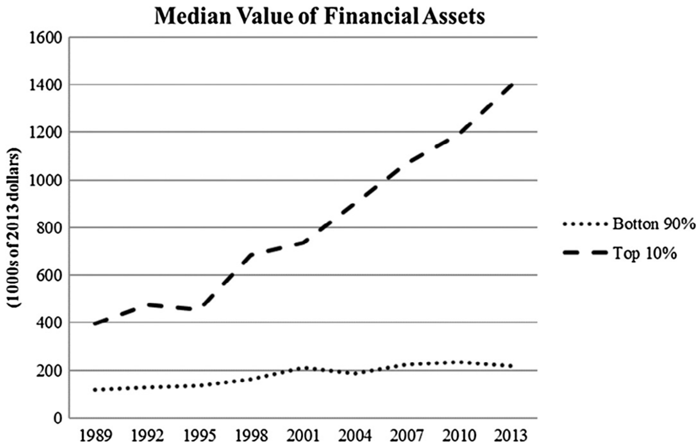

Fig. 9. Median value of financial assets.

of the income distribution as they are averaged out with lower earning families within the top 10% of earners. On the other hand, observing the fact that income from non-wage activities has been relatively stagnant for most of the households outside the upper end of the income distribution, we believe that low rates have made it easier for these households to accumulate debt relative to their income (likely mortgage debt). This has been accompanied with increases in debt service. Intuitively, increases in debt service have benefited debt providers (wealthy households), resulting in higher income disparity between debt holders and debt providers.

3. Data and methodology

3.1. Data

Annual S&P 500 and interest rate data were collected from the FRED database. Our annual measure of household debt data was taken from Philippon (2015). Philippon (2015) defined debt as the level of household debt normalized by output.[9] The annual data used for our measures of inequality were obtained from the World Wealth & Income Database due to its relatively long time-series. Piketty and Saez (2001) give a detailed description on how the top income shares are estimated. The top income shares are based on tax returns data published by the Internal Revenue Service (IRS). The income definition they use is a gross income definition including all the income items reported on tax returns (prior to deductions): salaries and wages, small business and farm income, partnership and fiduciary income, dividends, interest, rents, royalties, and other small items reported as other income. Then, the income shares are estimated by dividing the income amounts accruing to each top fractile by total personal income computed from the National Accounts. In this paper, we use the calculated top income shares including realized capital gains.[10]

[9] We used both measures of household debt available in Philippon (2015). Our results were nearly identical using either measure.

[10] An argument that has been raised since the publication of Piketty's book is that his data overestimates true inequality. Alvaredo (2011) shows that, in fact, most current survey based studies *underestimate* the true level of wealth held by top income earners.

Our first measure of inequality is probably the most familiar, the Gini coefficient, which summarizes the distribution of income into a single numerical index.[11] It ranges between 0 and 1, where 0 indicates perfect equality and 1 indicates that a tiny group owns all resources. One criticism regarding the Gini coefficient is that it does not let us clearly understand how much income is received by different groups within the income distribution. Particularly, we may miss much of the change occurring at the top of the income distribution. Therefore, we also look at the evolution of the shares of top centiles relative to the rest of income earners by constructing a Theil index using data on income shares for the top 1% and bottom 99% of income earners from the World Wealth & Income Database. This lets us better understand the disproportionate share of growth taken by the top end of the distribution as noted in Piketty (2014) and Gordon and Dew-Becker (2007). Additionally, we use the inverted Pareto-Lorenz coefficient, which measures income inequality between the top 1% and 0.1% of income earners (Piketty and Saez, 2001; Atkinson et al., 2011).

The Theil index provides a measure of the discrepancies between the distribution of income and the distribution of population between groups of individuals. If all population groups have an income share equal to their population share, the overall Theil index is zero. For instance, the top 1 percent of earners would get 1 percent of income and the bottom 99 percent of earners would get 99 percent of the income. As such, the index for the top 1% was constructed as follows:

$$T = I_{top1} \times |I_{top1} - N_{top1}| + I_{b99} \times |I_{b99} - N_{b99}| \tag{1}$$

where the *I's* indicate the income share of the various income percentiles and the *N's* indicate the size of the respective percentiles (here they would simply be 0.01 and 0.99). All data was collected for the 1919–2009 time period.

Looking at Fig. 10, we can see that relative to the other two inequality measures, the Gini coefficient has a lower variance and the slope of the series is much lower for the post 1980s period.

As mentioned above, this can lead the Gini coefficient to underestimate the true level of income inequality. By using three distinct measures of income inequality, we aim to show which income groups were most affected by changes in the financial variables we consider.

The length of our series is important as it allows us to observe inequality through different historical periods. Changes in the tax code and treatment of different types of income are important to note. For example, the 1980s saw significant changes in tax policy and in general economic policy during the Reagan administration. Particularly, 1986 is often singled out as a groundbreaking year in the tax literature due to the significant changes brought about by the Tax Reform Act. Also, perhaps the "Reagan Revolution", lower unionization, and financial deregulation had large impacts on inequality. The "Volcker disinflation" also occurred in the early 1980s which may have affected the income distribution. Levy and Temin (2007) provide further details on many institutional changes in the U.S. for the interested reader. In light of these concerns, to ensure our model is not misspecified, we test for structural breaks.

3.2. Methodology

We consider the following *4*-variable VAR (*p*),

$$Z_t = \sum_{i=1}^{p} \Phi_i Z_{t-p} + \varepsilon_t \tag{2}$$

such that Z_t' = [$\Delta Interest_t$, $\Delta S\&P_t$, $\Delta Debt_t$, $\Delta Inequality_t$] where $\Delta Interest_t$, $\Delta S\&P_t$, $\Delta Debt_t$,$\Delta Inequality_t$ are changes in the AAA Moody's Corporate bond rate, S&P 500, household debt as a percentage of RGDP, and the three inequality measures we consider.[12] $\varepsilon_{\sim}(0, \Sigma)$ is a vector of independent and identically distributed error terms. A lag length for (2) was selected using the Akaike Information Criteria and the Bayesian/Schwarz Information Criteria which both suggested $p = 1$. We chose to first estimate generalized impulse response functions and generalized variance decompositions that are invariant to the ordering of the variables. We also estimate a SVAR using a Choleski decomposition for robustness. Diebold and Yilmaz (2012) build upon Koop et al. (1996) and develop forecast error decompositions that are *invariant* to the variable ordering. As such, we implement both Koop et al. (1996) and Diebold and Yilmaz (2012) in order to generate generalized impulse response functions and generalized variance decompositions.

As noted in Diebold and Yilmaz (2012), the variance decompositions allow one to assess the fraction of the *H*-step-ahead error variance in forecasting z_i that is due to shocks to z_j, $\forall j \neq i$, for each *i*. Diebold and Yilmaz (2012) use the structure of Koop et al. (1996) to produce variance decompositions that are *invariant to the ordering of the variables* because of the use of the historically observed distribution of the errors. Given the uncertainty regarding the correct ordering of our variables, we follow Koop et al. (1996) and Diebold and Yilmaz (2012) and generate generalized impulse response functions and generalized variance decompositions. Diebold and Yilmaz (2012) define the own variance shares as the fraction of the H—step-ahead error variances in forecasting z_i that are due to shocks to z_i for $i = 1, 2, \ldots, N$ and cross variance shares as the fraction of the H—step-ahead error variances in forecasting z_i that are due to shocks to z_{ij} for $i, j = 1, 2, \ldots, N$ such that $i \neq j$. The Koop et al. (1996) H-step-ahead forecast error variance decompositions are

[11] The Gini coefficient does not include capital gains.

[12] For robustness we also used interest data on U.S. Treasuries that span a similar time period; however, our results were quantitatively and qualitatively similar. These findings are discussed further in the results section.

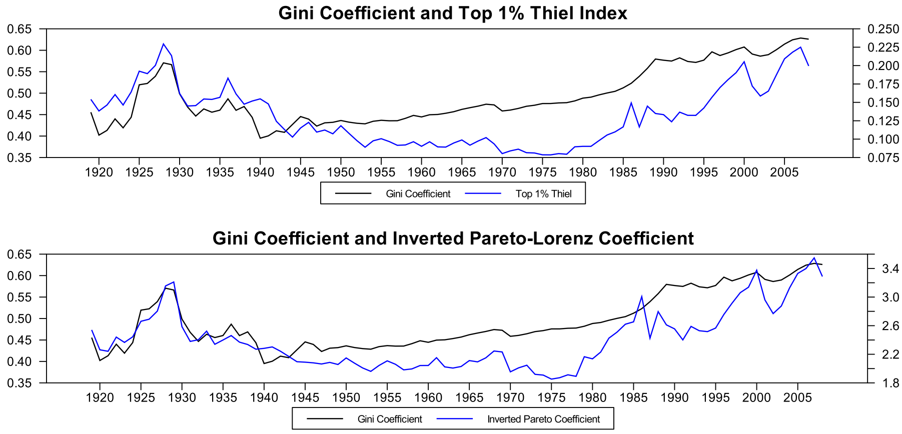

Fig. 10. Income inequality measures.

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1}\sum_{h=0}^{H-1}\left(e_i' A_h \sum e_j\right)^2}{\sum_{h=0}^{H-1}\left(e_i' A_h \sum A_h' e_i\right)} \tag{3}$$

where $\sum$ is the variance matrix for the error vector ε, σ_{jj} is the standard deviation of the error term for the jth equation, and e_i is the selection vector, with 1 as the ith element and zeros otherwise. Because the sum of the elements in each row of the variance decomposition table need not equal 1, Diebold and Yilmaz (2012) normalize each entry in the variance decomposition matrix by:

$$\tilde{\theta}_{ij}^{g}(H) = \frac{\theta_{ij}^{g}(H)}{\sum_{j=1}^{N}\theta_{ij}^{g}(H)} \tag{4}$$

such that by construction $\sum_{j=1}^{N}\tilde{\theta}_{ij}^{g}(H) = 1$. Diebold and Yilmaz (2012) then use the volatility contributions from the above generalized variance decomposition to construct the total spillover index as:

$$S^{g}(H) = \frac{\sum_{\substack{i,j=1\\ i\neq j}}^{N}\tilde{\theta}_{ij}^{g}(H)}{N} * 100 \tag{5}$$

Thus, the total spillover index measures the contribution of volatility shocks across the four variables in our VAR to the total forecast error variance. The directional volatility spillovers Diebold and Yilmaz (2012) subsequently layout provide a decomposition of the total spillovers to those coming from (or to) a particular variable. The volatility spillover received by variable i from all other variables j is

$$\frac{S_{i\cdot}^{g}(H) = \sum_{\substack{j=1\\ j\neq i}}^{N}\tilde{\theta}_{ij}^{g}(H)}{N * 100} \tag{6}$$

Similarly, the directional volatility spillovers transmitted by variable i to all other variables j is

$$\frac{S_{\cdot i}^{g}(H) = \sum_{\substack{j=1\\ j\neq i}}^{N}\tilde{\theta}_{ji}^{g}(H)}{N * 100} \tag{7}$$

The net spillover from variable i to all other variables j is

$$S_{i}^{g}(H) = S_{\cdot i}^{g}(H) - S_{i\cdot}^{g}(H) \tag{8}$$

The net pairwise volatility spillovers, are defined as

$$S_{ij}^{g}(H) = \frac{\tilde{\theta}_{ji}^{g}(H) - \tilde{\theta}_{ij}^{g}(H)}{N} * 100 \tag{9}$$

4. Results

Before estimating (2), we conduct unit root tests for all variables included in the VAR. As noted above, changes in the tax code or other political changes may have caused a structural break in the inequality time-series we use. To address the concern of a structural break in the inequality series', we utilized the two-break minimum LM unit root test that endogenously determines two structural breaks (T_B) in the level and trend developed by Lee and Strazicich (2003). All variables were found to contain unit roots and did not have structural breaks and were thus differenced.[13]

4.1. Impulse response functions

For ease of exposition, we standardized and cumulated the generalized impulse responses. Figs. 11–13 display the impulse responses from estimating (2) using the three different measures of income inequality. Fig. 11 displays the responses using the Gini coefficient as the income inequality measure, Fig. 12 displays the results using the Theil index, and Fig. 13 displays the results using the inverted Pareto coefficient. The figures should be read such that the column variable shocks the row variable.

Note, that while the point estimates are all negative, only for income inequality represented by the Top 1% Thiel index do changes in the interest rate have a statistically significant effect. The result suggests that a positive one standard deviation shock to the interest rate has a statistically significant, negative impact on income inequality which is approximately 0.25 standard deviations after five years. This implies that expansionary monetary policy increases income disparity between the top 1% and the bottom 99% income groups. One possible reason we may not see similar effects with the Gini coefficient and the inverted Pareto coefficient is that these two measures compare income groups that are more similar than different: the Gini primarily captures lower and middle income changes while the inverted Pareto coefficient captures changes at the very top of the income distribution. Another possible reason we see a significant response in the Top 1% Theil index from changes in the interest rate is that, as we presented in Section 2, a higher portion of income for households within the top 1% of earners is from interest rate sensitive assets. Put another way, high income earners have a higher interest rate elasticity of income than those at the bottom of the income distribution. If we look back to Fig. 5, income shares from realized capital gains for the period 1990–2009 doubled for households in the top 1% of the income distribution; whereas, for households in the bottom 90%, this source of income is almost zero. Similarly, wealthy households receive roughly 30% of their income from entrepreneurship (see Fig. 4). Thus, low rates may have helped high income earners to further expand their entrepreneurial activities and invest in financial markets, which has led to upsurges in their income shares.

Furthermore, comparing Figs. 3–5, it clearly suggests that sources of income that benefit from low interest rates (capital gains and entrepreneurship) dominate sources of income that are affected negatively by low rates (income from interest rates). We believe this is the reason why we capture an inverse relationship between interest rates and income inequality. Another plausible explanation, as presented by Doepke et al. (2015), is that low interest rates reflect low and stable rates of inflation, which mainly helps savers (households at the top of the income distribution) and harms debt holders (households at the middle and bottom of the income distribution). When capital gains are excluded from the top 1% income shares, the inverse relationship between the interest rate and the Top 1% Thiel index remained, but it was not statistically significant.[14]

Note in the second column of Figs. 11–13 that positive shocks to the stock market show statistically significant effects across the three measures of income inequality. Per one standard deviation increase in stock market returns, the Gini coefficient increases contemporaneously by 0.4 standard deviations. The Top 1% Theil index and the inverted Pareto coefficient increase by approximately 0.5 standard deviations. The magnitude of the relationship remains statistically significant, but drops by half when realized capital gains are excluded from the income inequality measures.

From the first column, we can see that positive shocks to the interest rate have an adverse effect on the stock market and household debt. Bordo and Landon-Lane (2013) document that "loose" monetary policy impacts asset prices positively and significance remains across different sub-periods. Interestingly, positive shocks in household debt as well as income inequality (across all three measures) have a statistically significant effect on stock returns by 0.25 and 1.0 standard deviations, respectively. This suggests that equity markets benefit from increased household debt as well as increased income inequality. These findings remain intact even after capital gains are excluded from the income inequality measures.

Note in the third column of Figs. 11–13 that a one standard deviation increase in household debt leads to statistically significant increases in income inequality across the measures that capture top income shares. After five years, income inequality is 0.5 standard deviations higher using the Top 1% Theil index and 0.4 standard deviations higher using the IPAR coefficient. The positive response of income inequality from increases in debt and equities is consistent with the idea that top earners use a substantial portion of their income to accumulate financial wealth through loans to those at the low end of the income distribution as in Kumhof and Ranciere (2013). The findings are consistent when capital gains are excluded from the measures. Interestingly, changes in household debt show no statistically significant effect on the variation of the Gini coefficient. One possible explanation is that the Gini coefficient mainly captures income inequality in the middle of the income distribution. As we saw in Section 2, these households hold roughly similar levels of debt relative to their income. Thus, income disparity among the households outside the top end of the income distribution is not responding to the changes in household debt.

One criticism of generalized impulse responses is that, if the responses are highly correlated, the shocks are almost impossible to interpret reasonably. As such, as a robustness test, we estimated (2) using a Choleski decomposition of the

[13] Results may be obtained upon request of the authors.

[14] The findings based on income inequality measures that exclude capital gains are available upon request.

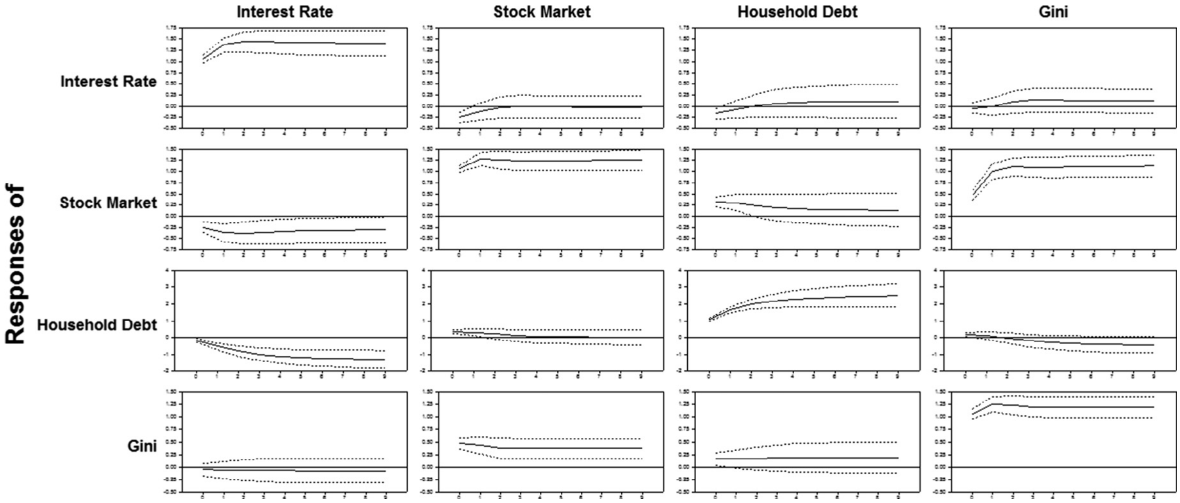

Fig. 11. Generalized impulse responses using gini coefficient as income inequality measure.

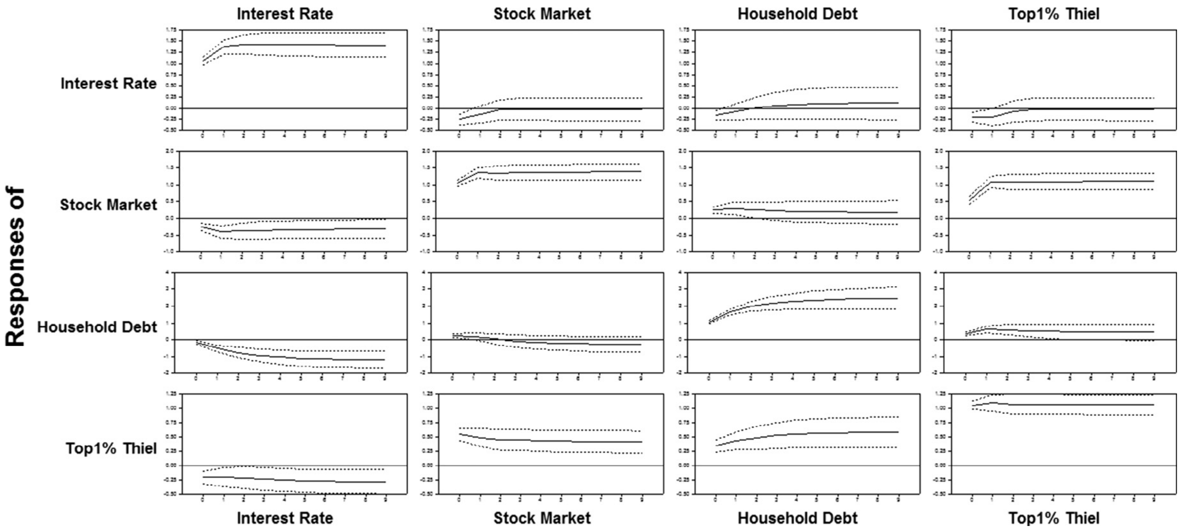

Fig. 12. Generalized impulse responses using 1% theil index as income inequality measure.

covariance matrix. Figs. 14–16 display the results from estimating (2) using a Choleski decomposition, where the AAA Moody's Corporate bond rate is used as the interest rate variable.

In addition, we also estimated (2) using changes in the 10-year Treasury bond rates as an alternative to the AAA Corporate bond rate since most households possess mortgage debt and mortgage rates are tightly tied to the 10-year Treasury bond rates (and most of the investments are long term). The results were nearly identical and may be obtained upon request of the authors.

The inverse relationship between interest rates and income inequality identified from the empirical results is contrary to the results obtained by Coibion et al. (2012). We believe that differences in the data sources and the length of the time-series used might lead to the different results found in this paper. The income inequality measures calculated by Coibion et al. are based on the income data reported in the Consumer Expenditure Survey and the series are available only from 1980. We use the income data from the World Wealth & Income Database, which allows us to perform the analysis starting from 1919. Also, it should be noted that the income data from the Consumer Expenditure Survey does not include household incomes that are at the upper end of the income distribution, such as the top 1% of income earners. The upper income in Coibion et al.'s analysis is defined by household income at the 90th percentile.[15] Two of our income inequality measures capture

[15] Specifically, Coibion et al. (2012) use the Gini coefficient and the ratio of earnings of the 90th percentile of earners to the 10th percentile of earners (p. 8–10).

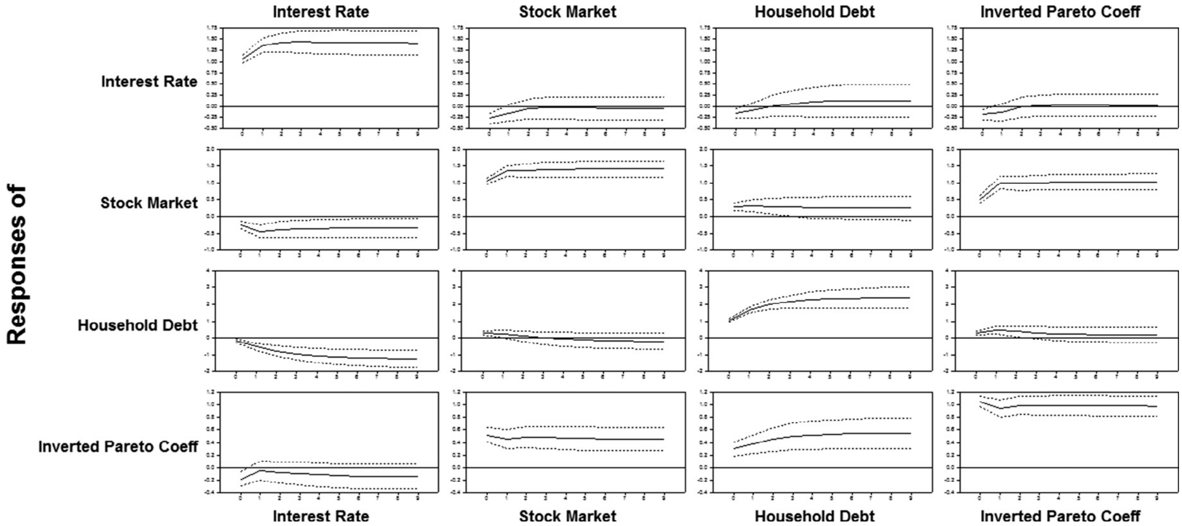

Fig. 13. Generalized impulse responses of income inequality using inverted pareto coefficient as income inequality measure.

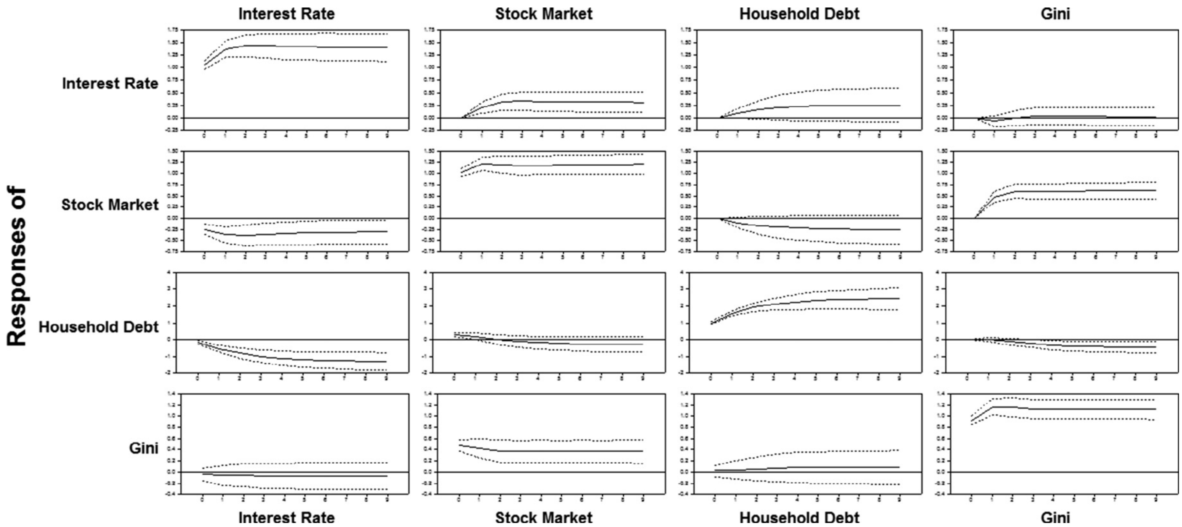

Fig. 14. Choleski decomposition: impulse responses using gini coefficient as income inequality measure.

income shares at the upper end of the income distribution: the Top 1% Thiel index and the inverted Pareto coefficient. As we saw from Section 2, within the top 10%, it is the top 1% and top 0.1% of earners that have benefited the most during the last 30 years. As seen in Fig. 1, the income shares of the households in the top 9% of the income distribution increased roughly 2% between 1980 and 2007. Over the same period, the income share of the top 1% more than doubled and the income share of the top 0.1% almost quadrupled. Thus, we believe that the income sources of a household at the 90th percentile of the income distribution are very different from the income sources of a household in the top 1% (99th percentile) or the top 0.1% (99.9th percentile) of earners. Lastly, there are differences in the measures of income used in constructing the income inequality measures that might contribute to differences in the results between this paper and Coibion et al.'s. Total income from Coibion et al. includes transfers for each household and does not include realized capital gains. The income measures from the World Wealth & Income Database include all the income items reported on tax returns (prior to deductions) and do not include transfers.

4.2. Generalized variance decompositions

Table 1 Panel A displays the Diebold and Yilmaz (2012) generalized variance decompositions using the Gini coefficient as the measure of inequality.[16]

[16] Since the results are similar across the two interest rate measures, we only report the findings when the AAA Moody's Corporate bond rate is used as the monetary policy variable.

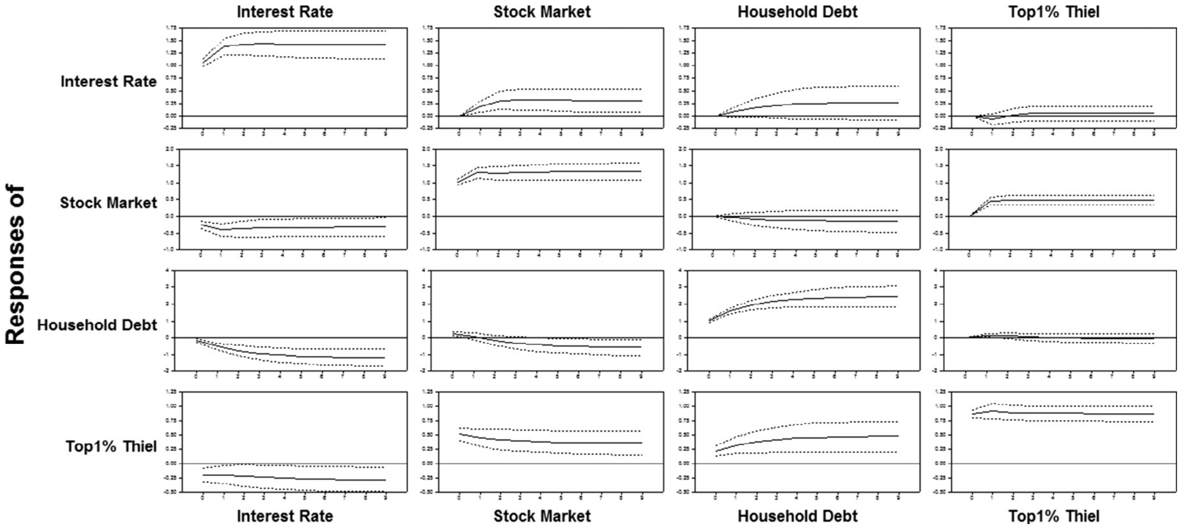

Fig. 15. Choleski decomposition: impulse responses using 1% theil index as income inequality measure.

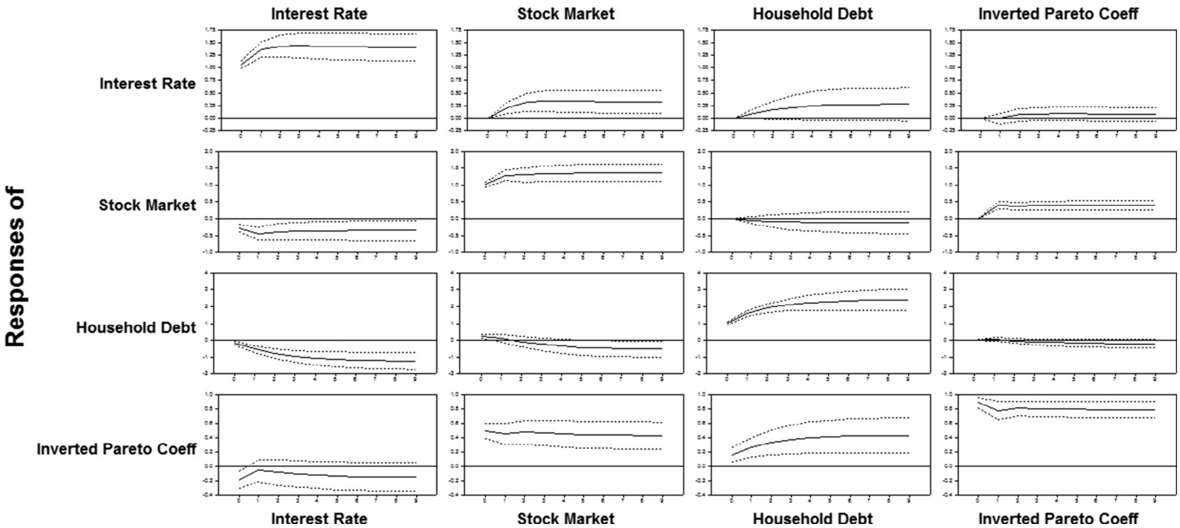

Fig. 16. Choleski decomposition: impulse responses of income inequality using inverted pareto coefficient as income inequality measure.

As can be seen in the last column of Table 1 Panel A, a substantial portion of the variation in the stock market, household leverage, and the Gini coefficient are attributed to the other variables in the VAR. 4.4% of the variation in the stock market returns is accounted for by the interest rate, 6.6% by household leverage, and 27.8% by the Gini coefficient. As can be seen in row 3 of Table 1 Panel A, 13.5% of the variation in household debt is attributed to the interest rate, 6.5% to the stock market, and 3.9% to the Gini coefficient. In row 4, note that 17.3% of the variation in the Gini coefficient is explained by the stock market, 2.6% is explained by household leverage, and 0.3% is explained by the interest rate. In sum, 20% of the variation in the Gini coefficient is explained by the financial variables in the VAR. The Gini coefficient accounts for a total of 33% of the variation in the other variables in Table 1 Panel A. As discussed before, the Gini coefficient is more sensitive to changes in the lower to middle income groups. If these groups have seen relatively little movement in income over broad sections of time, then this measure may not fully capture changes at the top of the income distribution. Still, given the limitations of the Gini coefficient, we see some evidence that equity markets matter in regards to inequality.

Table 1 Panel B displays the Diebold and Yilmaz (2012) generalized variance decompositions using the Top 1% Theil index as the measure of inequality.

As can be seen in the last column of Table 1 Panel B, much of the variation in the stock market, household leverage, and Top 1% Theil index is attributed to the other variables in the VAR. 4.6% of the variation in stock market returns is accounted for by the interest rate, 4.9% by household leverage, and surprisingly, 28.4% by the Top 1% Theil index measure. As can be

Table 1
Diebold and Yilmaz (2012) generalized variance decompositions.

	Interest Rate	S&P 500 Returns	Household Debt	Gini	From Others
Panel A (Gini)					
Interest Rate	88.5	6.8	3.6	1.1	11.0
S&P 500 Returns	4.4	61.2	6.6	27.8	39.0
Household Debt	13.5	6.5	76.2	3.9	24.0
Gini	0.3	17.3	2.6	79.8	20.0
Contribution to Others	18.0	31.0	13.0	33.0	
	Interest Rate	S&P 500 Returns	Household Debt	1% Theil Index	From Others
Panel B (Top 1% Thiel Index)					
Interest Rate	86.2	6.5	3.2	4.0	14.0
S&P 500 Returns	4.6	62.1	4.9	28.4	38.0
Household Debt	11.7	5.3	74.0	9.0	26.0
1% Theil Index	2.7	18.2	8.8	70.3	30.0
Contribution to Others	19.0	30.0	17.0	41.0	
	Interest Rate	S&P 500 Returns	Household Debt	Inverted Pareto Coeff.	From Others
Panel C (IPAR)					
Interest Rate	86.0	7.2	3.4	3.4	14.0
S&P 500 Returns	5.5	63.3	5.9	25.3	37.0
Household Debt	12.4	5.9	75.8	5.9	24.0
Inverted Pareto Coeff.	3.3	16.7	7.0	73.0	27.0
Contribution to Others	21.0	30.0	16.0	35.0	

seen in row 3 of Table 1 Panel B, 11.7% of the variation in household debt is attributed to the interest rate, 5.3% to the stock market, and 9% to the Top 1% Theil index. In row 4 of Table 1 Panel B, note that 18.2% of the variation in the Top 1% Theil index is explained by the stock market, 8.8% is explained by household leverage, and 2.7% is explained by the interest rate. In sum, 30% of the variation in the Top 1% Theil index is explained by the financial variables in the VAR.

Our inequality measure accounts for a total of 41% of the variation in the other variables in Table 1 Panel B. Recall that the Top 1% Theil index is capturing the discrepancy between the top 1% and bottom 99% of earners. Note that the income inequality measure accounts for 28.4% of the variation in stock market returns. This provides support for the idea that the top 1% participate more in the stock market meaning, that as more income is distributed to the top 1%, more income flows into the stock market. Additionally, note that household debt and the stock market explain a fairly large amount of variation in the Top 1% Theil index, providing evidence for an equity and debt channel in regards to inequality. In addition, the interest rate explains a large part of household debt, further supporting the debt channel of monetary policy impacting income inequality.

Table 1 Panel C displays the generalized variance decompositions of income inequality using the inverted Pareto coefficient as the measure of inequality.

As seen in the last column of Table 1 Panel C, other variables explain 37% of variation in the stock market, with 5.5% attributed to the interest rate, 5.9% attributed to household leverage, and 25.3% attributed to the inverted Pareto coefficient. In row 3 of Table 1 Panel C, we see that 12.4% of the variation in household leverage is attributed to the interest rate, 5.9% is attributed to the stock market, and 5.9% is attributed to the inverted Pareto coefficient. In total, 24% of the variation in household leverage is explained by other variables. In row 4, we see that 3.3% of the variation in the inverted Pareto coefficient is explained by the interest rate, 16.7% is explained by the stock market, and 7% is explained by household leverage. Overall, 27% of the variation in the inverted Pareto coefficient is explained by the financial variables. Correspondingly, the inverted Pareto coefficient explains roughly 35% of the variance in the financial variables.

5. Conclusion

We have provided a long-run analysis describing the relationship between three key financial variables (interest rates, household debt, and equity returns (S&P 500)) and three measures of income inequality. We believe the longer time period used in this paper, from 1919 to 2009, gives us an advantage relative to other studies because the longer span of data allows us to observe the long-run response of inequality. We provide evidence for the different channels affecting inequality by analyzing how households earn their income. Using Philippon's (2015) household debt data, we show that the stock market and household debt have significant effects on income dispersion in the United States. Interest rates have a direct effect only when we consider the Top 1% Thiel index. In summary, our results suggest that household debt and equities are inversely related to interest rates and associated with higher levels of income inequality. This provides supporting evidence for Kumhof and Ranciere's (2013) debt-to-income inequality hypothesis and Stiglitz's (2015) equity-to-income inequality hypothesis. Also, we document a direct link between increases in income inequality, defined as the income disparity between the top 1% and bottom 99% income groups, and low interest rates. The significance dropped when capital gains were excluded from the income shares. As such, we believe that our results suggest that low interest rates can exacerbate income inequality primarily because high income households derive a larger portion of their income from interest rate sensitive sources rather than wages. There may be additional explanations and our analysis is an attempt to help shed light on a few potential causes of inequality.

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