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Abstract

We study the distributional consequences of uncertainty shocks in the U.S. economy at a business cycle frequency. We document that the effects of uncertainty shocks are highly heterogeneous across income and wealth distribution and also vary depending on the sources of uncertainty. First, uncertainty shocks tend to have a more adverse effect on income at the top and bottom of the distribution spectrum resulting in narrower income inequality between the rich and the middle class but wider inequality between the middle class and the poor. Second, once the redistribution policy is considered, uncertainty shocks do reduce income inequality. Third, the distributional consequences for wealth differ from those for income, as uncertainty shocks are relatively beneficial to both the middle class and the poor. Fourth, the COVID-19 pandemic has brought different implications on wealth inequality between Wall Street and Main Street uncertainty; whereas the former reduces wealth inequality through its particularly adverse effect on risky asset prices, the latter uncertainty increases it by damaging the labor market.

JEL Classification: E31; E32; E62; F31; F41

Keywords: Uncertainty shocks; Income inequality; Wealth inequality; Redistribution policy; COVID-19

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I. Introduction

The global financial crisis and the recent COVID-19 pandemic have been characterized by an unprecedented level of uncertainty about the future course of the economy. In this context, policymakers and economists worldwide are concerned about the distributional consequences of these events because not everyone is equally affected by these adverse shocks (De Haan and Sturm, 2017; Deaton, 2021; Stantcheva, 2022). Many theoretical studies model uncertainty as a dispersion of exogenous shocks (e.g., productivity, preference, or policy shocks) that impact the economy (Bloom, 2009; Basu and Bundick, 2017; Fernández-Villaverde and Guerrón-Quintana, 2020), and thus an increase in uncertainty may lead to a greater dispersion of economic outcomes such as consumption, income, and wealth, translating into rising inequality.[1] If this is the case, it would provide policymakers with further impetus to alleviate the adverse effects of uncertainty shocks.[2]

However, there has been limited empirical evidence on the link between uncertainty and inequality, which is surprising given the rapid progress in measuring uncertainty and understanding its macroeconomic effects, as summarized in Bloom (2014). Even recent survey papers on the determinants of inequality have not paid attention to the role of uncertainty in driving inequality (Tridico et al., 2018; Colciago et al., 2019; Furceri and Ostery, 2019). Most prior studies on the cyclical drivers of inequality have focused on various policy changes, especially changes in monetary policy (Coibion et al., 2017; Mumtaz and Theophilopoulou, 2017; Furceri et al., 2018; Auclert, 2019;

[1] For example, theoretical studies such as Kasa and Lei (2018) and Jovanovic and Ma (2022) present a mechanism in which an increase in uncertainty leads to an increase in the top wealth shares and a more dispersed distribution of outcome growth, thereby contributing to rising inequality. Moreover, income inequality has been shown to increase during economic downturns (Heathcote et al., 2010; Meyer and Sullivan, 2013). To the extent that recessions are often associated with heightened uncertainty, one can expect that uncertainty shocks increase income inequality.

[2] Although uncertainty shocks can make monetary or fiscal policy less effective by increasing the option value of waiting (Bloom, 2009), policymakers can improve structural factors interacting with uncertainty shocks. For example, financial frictions and labor search frictions are found to amplify the adverse effect of uncertainty shocks (Leduc and Liu, 2016; Schaal, 2017; Alfaro et al., 2018; Alessandri and Mumtaz, 2019; Fernández-Villaverde and Guerrón-Quintana, 2020), which call for policy efforts to alleviate these frictions.

Amberg et al., forthcoming; Samarina and Nguyen, forthcoming) and, to a lesser extent, fiscal policy (García-Peñalosa and Turnovsky, 2007; Anderson, 2017).

This gap in the literature is largely attributed to the lack of sufficient high-frequency data, especially for wealth inequality, given the mostly short-lived nature of uncertainty shocks (Bloom, 2009). Indeed, to the best of our knowledge, there are only three published papers (De Giorgi and Gambetti, 2017; Fischer et al., 2021; Theophilopoulou, 2021) that empirically investigate the effect of uncertainty shocks on income inequality as of the writing of this paper and none on wealth inequality.[3] We seek to fill this gap in the literature by providing a systematic empirical analysis of how uncertainty shocks have affected both income and wealth inequality in the United States over the past four decades.

Compared with the previous studies discussed above, our work has several distinguishing aspects. First and most importantly, none of these studies investigated the effect on wealth inequality because of the difficulty in measuring wealth distribution. Second, the measure of income and wealth inequality in our analysis is available at a monthly frequency and consistently for over 45 years, yielding substantially more observations than used in previous studies. Such monthly frequency data alleviate the concern about identifying structural shocks when using Cholesky ordering and help reveal interesting short-run dynamics of inequality following the uncertainty shock.

Third, the inequality metrics used in our analysis contain information about individual income and wealth at the very right tail of the distribution, the so-called super-rich (e.g., top 0.1%

[3] De Giorgi and Gambetti (2017) estimated the effect of three different types of uncertainty shocks on consumption inequality in the United States using CEX data from 1984Q1 to 2010Q4. They found that consumption inequality falls after the uncertainty shock, especially due to a larger consumption reduction by the 10^{th} decile. Fischer et al. (2021) studied the state-level response of income inequality to nationwide uncertainty shocks in the United States from 1985Q1 to 2017Q1. When using the Gini coefficient as a measure of income inequality, they found that uncertainty shocks reduce income inequality in most regions. Theophilopoulou (2021) estimated the impact of uncertainty shocks on income, wage, and consumption inequality in the United Kingdom from 1970Q1 to 2018Q1. She found that wage and income inequality decline following the uncertainty shock.

or 0.01%), which was usually not available in previous studies based on a survey. Since capital gains, as well as capital and business income, are major sources of total income for this group, the effect of uncertainty shocks on this group might differ from that on the top 10%, whose income still largely depends on labor income. Fourth, we investigate whether our findings depend on the source of uncertainty by comparing the effects of financial (or Wall Street) uncertainty with those of macroeconomic (or Main Street) uncertainty. Fifth, we compare the responses of market income and disposable income to uncertainty shocks to shed light on the interaction between the uncertainty shock and redistribution policy. Finally, we estimate the effect of uncertainty shocks on income and wealth inequality with and without the recent COVID-19 pandemic to determine whether this unprecedented event affects our findings.

We analyze the dynamic effect of uncertainty shocks on income and wealth inequality by estimating a structural vector autoregression (VAR) model of the U.S. economy from 1976M1 to 2019M12. Given the erratic nature of the data during the pandemic, we did not use them in the baseline analysis. However, we include this period in the extended analysis to shed light on whether the pandemic has affected the link between uncertainty and inequality. In addition to the standard macroeconomic and financial variables characterizing the U.S. economy, our VAR model includes the real income and wealth share of different groups. These income and wealth inequality measures were taken from Blanchet et al. (2022), who recently constructed distributional data on income and wealth at a monthly frequency, building on their prior work using annual data (Saez and Zucman, 2016; Piketty et al., 2018). These high-frequency data allow us to study both the short- and medium-term dynamics of inequality in response to uncertainty shocks.

We find that uncertainty shocks have heterogeneous effects across income and wealth groups, resulting in changes in inequality. However, different inequality metrics do not always lead to the same conclusion, a caveat emphasized by Heathcote et al. (2010). This finding highlights the importance of evaluating the entire distribution when assessing the effects of uncertainty shocks on inequality. Regarding income inequality, the rich (top 10%) and poor (bottom 50%) are more adversely affected by uncertainty shocks than the middle class (middle 40%). As a result, the top 10% share of income decreases, while the top 50% share of income increases, indicating that we obtain different implications of uncertainty on inequality depending on its exact definition.

However, the distributional consequence of uncertainty shocks changes once we incorporate the interaction with the redistribution policy by examining the response of disposable income instead. In this case, uncertainty shocks tend to lower income inequality across the distribution, alleviating the concern that rising uncertainty widens income inequality. Regarding wealth inequality, the poor are less negatively affected than the rich or the middle class, which is in contrast to the results for income inequality using market income. A very low level of wealth (often negative) of the poor and a redistribution policy particularly benefitting the poor can explain this finding. Although the estimated effects are not precise enough to draw a firm conclusion, uncertainty shocks do not appear to increase wealth inequality.

To shed light on the channel through which uncertainty affects inequality, we carefully examine how the estimated effects depend on the source of uncertainty. We compare the effects of uncertainty in financial markets with those of the macroeconomy. We find that both types of uncertainty shocks have similar qualitative effects on income inequality but distinct effects on wealth inequality, especially once the COVID-19 pandemic is included in the analysis. The wealth of the rich is particularly vulnerable to financial uncertainty, whereas that of the middle class is susceptible to macroeconomic uncertainty.

Such a distinction is driven by the divergence between the so-called "Wall Street" and "Main Street" uncertainty documented by Pastor and Veronesi (2017). To the extent that Wall Street uncertainty is largely a concern of the rich holding risky financial assets, one can rationalize why Main Street uncertainty is particularly damaging to the middle class, especially through labor markets, and contributes to rising wealth inequality during the pandemic, whereas Wall Street uncertainty tends to decrease wealth inequality.

The remainder of this paper is organized as follows. Section II explains the main data, including new high-frequency metrics of income and wealth inequality and various uncertainty measures, and introduces the empirical model. Section III presents the main findings and provides a series of robustness checks and extended exercises. Section IV concludes.

II. EMPIRICAL FRAMEWORK

A. Data

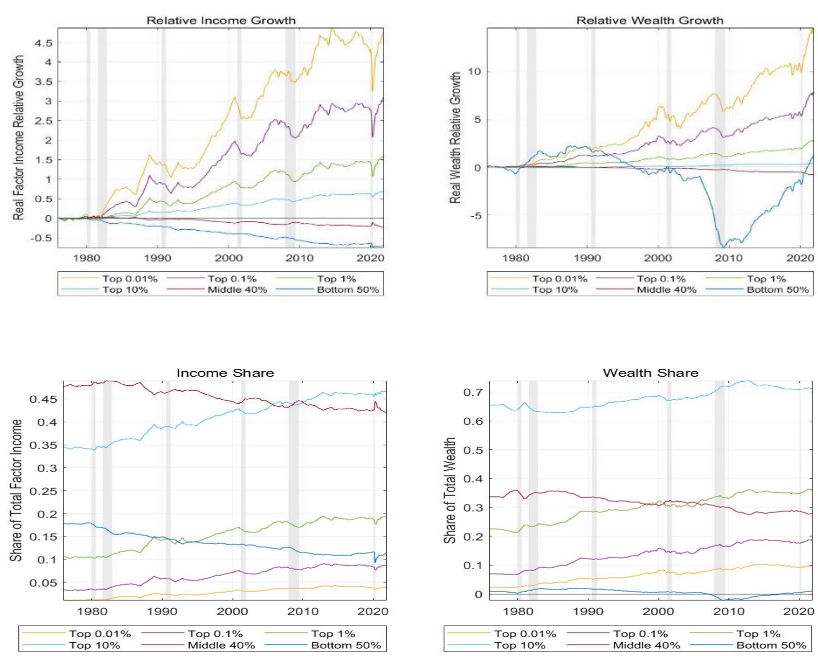
In this section, we describe the data used for our empirical analysis of the U.S. economy, with special attention to newly available high-frequency inequality data and various empirical proxies for uncertainty.

Measures of inequality. Our measures of inequality are based on monthly income and wealth distribution data, recently constructed by Blanchet et al. (2022). These data are publicly available at https://realtimeinequality.org/ and are updated regularly after the main national income statistics become available. They are analytic micro-level data that match national accounts the underlying data sources of which include the Internal Revenue Service (IRS), Bureau of Labor Statistics (BLS), Bureau of Economic Analysis (BEA), and Department of Labor (DOL). Using these data, one can track the monthly national income and wealth distribution. The series is adjusted for inflation, using 2021 as the base year, resulting in real values of income and wealth.

Blanchet et al. (2022) take a moving average of distributional national accounts annual microdata and rescale each income and wealth component to monthly data. This method is suitable for non-labor income parts because short-term gross changes mostly cover the distributional changes for each component. The distributional changes in non-labor income and wealth move slower than aggregate changes. However, labor income still accounts for approximately 75% of the national income, and its distribution can rapidly change. To consider fast-moving distributions due to changes in employment and wage earnings among different industries and counties, we use monthly employment data and quarterly specific wage distributions from the BLS Quarterly Census of Employment and Wages.

For the income inequality measure in this study, we use household factor income, which covers all capital and labor income before taxation and adds up to the national income. We also use disposable income to study the interaction between uncertainty shocks and redistribution policies. For the wealth inequality measure, we use all marketable wealth held by households. Funded pensions were included and debts were subtracted. Vehicles and unfunded pension promises were excluded from the wealth data. The sample period for these inequality data is January 1976 to December 2021. The data are reported for six groups, which are the top 0.01%, top 0.1%, top 1%, top 10%, middle 40%, and bottom 50%. The corresponding income or wealth ranking defines these groups.

Figure 1. Evolution of income and wealth of different groups over time



Note: The top panel plots the relative growth of income (left) and wealth (right) across groups, while the bottom panel plots the relative share of income (left) and wealth (right). The NBER recession period is represented by the shaded areas. The sample period was January 1976 to December 2021.

The top panel of Figure 1 shows the relative real income growth (left) and real wealth growth (right) for each group during the sample period. Growth rates were normalized to zero at the beginning of the sample period (1976M1). The relative growth for each group was computed as the difference between the group-specific growth rate and total growth rate. By construction, relative growth directly indicates how different income (or wealth) groups have performed compared to others over time.

There has been a strong trend of increasing inequality in income, as is apparent from the widening gap in growth between the rich and poor. This is consistent with prior observations that U.S. inequality has accelerated since the 1980s (Piketty et al., 2018). Real income growth tends to slow across business cycles during recessions, but with varying magnitudes. Real income growth at the right tail of the distribution appears to tend to fall more during recessions than other groups, especially during the recent pandemic.

Real wealth growth shows a different picture. While other groups share a broadly similar trend in the case of income growth, wealth growth of the bottom 50% behaves quite differently. The wealth growth of the poor was faster than the top 10% or the middle 40% until the early 1990s; then, there was a sharp change in this trend that lasted until the Great Recession. Since then, there has been some reversal, so the wealth growth of the poor, and therefore their wealth share, has somewhat recovered.

Interestingly, the pandemic accelerated the wealth growth of the very rich (top 1% or above), although it caused a greater reduction in the income growth of the same group, suggesting that the pandemic has sharply different implications for income and wealth distributions. Although our baseline analysis excludes the pandemic due to the erratic behaviors of many economic and financial variables, we extend the analysis by including this particular period to illustrate how this unprecedented event affected the uncertainty–inequality relationship.

The evolution of relative growth in income or wealth is not the only metric that captures the inequality dynamics over time. One might better understand how uncertainty shocks affect inequality by examining different groups' share of income or wealth (Figure 1, bottom panel). In addition to the Gini coefficient that largely captures lower and middle-income changes, the top 10%, middle 40%, and bottom 50% share of income or wealth jointly characterize the overall inequality level of the economy. It is apparent that the top 10% share of both income and wealth has increased over the past 45 years, whereas those of the middle 40% have steadily decreased. Simultaneously, there are meaningful fluctuations in this share over business cycles, suggesting that cyclical changes in inequality must not be overlooked.

Measures of uncertainty. Uncertainty is inherently unobservable; therefore, empirical proxies are necessary to investigate how uncertainty shocks affect income and wealth inequality. Recent empirical studies have generally constructed a variety of uncertainty measures by (i) employing forward-looking financial variables, especially from option prices (for example, the VIX index in Bloom, 2009), (ii) estimating forecast errors or stochastic volatility common to various macroeconomic and financial variables (Jurado et al., 2015; Carriero et al., 2018), (iii) applying a text-mining technique to search for uncertainty-related words in newspapers or other documents (Baker et al., 2016; Ahir et al., 2022), and (iv) measuring forecast dispersion or disagreement among survey respondents (Lahiri and Sheng, 2010; Bachmann et al., 2013). The rapid expansion of the literature on the effect of uncertainty shocks would not have occurred without recent improvements in measuring uncertainty. Because each method has advantages and disadvantages, the literature has typically considered multiple measures of uncertainty to draw robust conclusions.[4]

To shed further light on how the source of uncertainty matters in shaping its effect on inequality, we use various empirical measures of uncertainty to capture different aspects of the economy. In our baseline analysis, we employ two widely used measures of uncertainty (i.e., JLN

[4] See Cascaldi-Garcia et al. (forthcoming) for a comprehensive review of the literature on measuring uncertainty.

uncertainty) in the literature, that is, the financial and macroeconomic uncertainty indexes (Jurado et al., 2015), which were constructed using the same econometric model but intended to capture different sources of uncertainty (i.e., financial vs. macroeconomic origin). We use them as a baseline measure because they are directly comparable with each other and are available for the entire sample period of the study (1976M1–2021M12). Moreover, Kozeniauskas et al. (2018) show that among various uncertainty measures, the JLN indices have the highest overall correlation with other measures. As a robustness check, we employ other widely used measures of uncertainty, the VIX and Economic Policy Uncertainty index (Baker et al., 2016), which are available for shorter periods than the baseline measures (from 1990 and 1985, respectively).

The JLN uncertainty indices have been widely used in subsequent studies mainly because of their model-independent nature. While constructing these measures, the authors emphasize that the predictability of the economy is important in economic decision-making, rather than the variability of specific economic indicators, *per se*. Their financial (macroeconomic) uncertainty index is measured by the weighted sum of the individual uncertainty in the underlying financial (macroeconomic) variables. Individual uncertainty is constructed using the conditional volatility of the unforecastable component of the series in the future, removing the forecastable component.

Specifically, the JLN financial uncertainty U_t^F was constructed by aggregating a large number of individual uncertainties from a panel of financial data. Let $y_{j,t}^F \in Y_t^F = (y_{1,t}^F, \dots, y_{N,t}^F)'$ be a variable in a set of large financial series denoted by Y_t^F. For each macro series $y_{j,t}^F$, its h-period ahead uncertainty, denoted by $u_{j,t}^F(h)$, is defined as the volatility of the purely unforecastable component of the future value of the series, conditional on all available information:

$$u_{j,t}^F(h) \equiv \sqrt{E\left[\left(y_{j,t+h}^F - E[y_{j,t+h}^F|I_t]\right)^2|I_t\right]}, \tag{1}$$

where I_t denotes the information available up to time t. Then, h-period ahead financial uncertainty $U_t^F(h)$ is an aggregate of individual uncertainty measures across all financial series:

$$U_t^F(h) \equiv \underset{N\to\infty}{plim} \sum_{j=1}^{N} \frac{1}{N} u_{j,t}^F(h) \equiv \mathrm{E}[u_{j,t}^F(h)]. \tag{2}$$

Jurado et al. (2015) used 147 monthly financial time series to construct JLN financial uncertainty.[5] The JLN macroeconomic uncertainty U_t^M is constructed in the same way, but using 134 monthly macroeconomic time series.[6] We use one-month ahead (h=1) uncertainty as our baseline measure of uncertainty, but the key results still hold when using one-quarter (h=3) or one-year (h=12) ahead uncertainty.

Following much of the literature since Bloom's (2009) seminal work, we also use the implied volatility of the stock market as a measure of uncertainty for a robustness check. In particular, we use the VIX (implied volatility of S&P500). According to Bloom (2009), in general, after major shocks, the VXO index tends to temporarily jump about twice on average. The VIX largely captures uncertainty in financial markets, and its real-time availability makes it one of the most common measures of uncertainty.

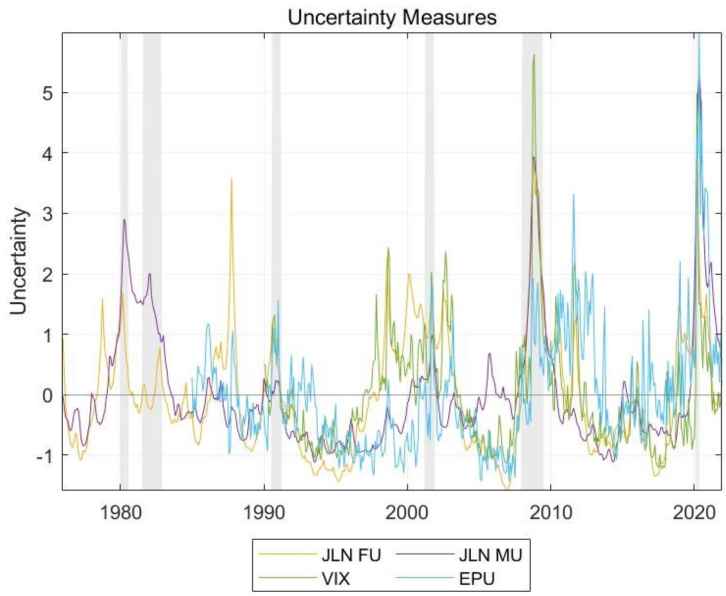
As the last measure of uncertainty, we use the economic policy uncertainty (EPU) index from Baker et al. (2016). According to Baker et al. (2016), their EPU index captures the uncertainty about "who will make economic policy decisions, what economic policy actions will be undertaken and when they will be enacted, the economic effects of past, present, and future policy actions, and uncertainty induced by policy inaction." (pp. 1,598). Baker et al. (2016) adopted a narrative approach to construct the index, using the news coverage of policy-related economic uncertainty by including articles containing terms related to economic and policy uncertainty from 10 large

[5] They include the dividend–price and earnings–price ratios, growth rates of aggregate dividends and prices, default and term spreads, yields on corporate bonds of different rating grades, yields on treasuries and yield spreads, and a broad cross-section of industry, size, book-to-market, and momentum portfolio equity returns.

[6] They include real output and income, employment and hours, real retail, manufacturing and trade sales, consumer spending, housing starts, inventories and inventory sales ratios, orders and unfilled orders, compensation and labor costs, capacity utilization measures, price indexes, bond and stock market indexes, and foreign exchange measures.

newspapers in the United States.[7] We use the U.S. EPU index, and the sample period is January 1985 to December 2021.

Figure 2. Evolution of uncertainty measures



Note: This graph plots the evolution of four uncertainty measures: JLN financial uncertainty, JLN macroeconomic uncertainty, the VIX, and EPU. All uncertainty measures in the figure were standardized to have zero mean and unit variance. The sample period for financial and macroeconomic uncertainty is January 1976 to December 2021; for the VIX, January 1990 to December 2021; and for the EPU index, January 1985 to December 2021.

Figure 2 presents the evolution of the four uncertainty measures, which were standardized for ease of comparison. A well-known fact regarding these uncertainty measures is their commonality. All uncertainty measures tend to spike during episodes with heightened uncertainty, such as the global financial crisis or the COVID-19 outbreak. Nevertheless, the correlation among them is not perfect, as shown in Table 1, suggesting that they still capture different aspects of uncertainty about the U.S. economy (Kozeniauskas et al., 2018).

[7] Each article should contain terms related to the three categories of uncertainty, economy, and policy to meet the criteria for inclusion. For example, an article containing the words "uncertain," "Congress," and "economic" meets the criteria.

Table 1. Correlation matrix for the uncertainty measures

	JLN FU	JLN MU	VIX	EPU
JLN FU	1			
JLN MU	0.577	1		
VIX	0.819	0.543	1	
EPU	0.442	0.564	0.453	1

Note: This table summarizes the correlation between the four uncertainty measures: JLN financial uncertainty, JLN macroeconomic uncertainty, VIX, and EPU. The correlation was calculated for each pair, and the common sample period was used for the calculation.

To more easily interpret the economic implications of our findings, we grouped these four uncertainty measures into two categories depending on the source of uncertainty: financial or macroeconomic. This grouping choice is motivated by the recent finding that the transmission of uncertainty shocks can differ depending on whether they have a financial or macroeconomic origin (Caldara et al., 2016; Ludvigson et al., 2021; Choi and Yoon, 2022). The JLN financial uncertainty index and VIX have a high correlation of 0.82, whereas the EPU index has the highest correlation (0.56) with the JLN macroeconomic uncertainty index, validating our grouping of the uncertainty measures.

Other macroeconomic and financial variables. We included a standard set of macroeconomic and financial variables in the VAR model. The choice of variables closely follows existing studies on the effect of uncertainty shocks on the U.S. economy (Bloom, 2009; Caldara et al., 2016; Leduc and Liu, 2016; Basu and Bundick, 2017; Choi and Yoon, 2022). The set of variables used in the baseline model includes the level of the U.S. stock market index (S&P500), industrial production, consumer price index (CPI), and the federal funds rate, combined with the Wu–Xia shadow rate (Wu and Xia, 2016) for the ZLB period, which are available at a monthly frequency.

B. Vector Autoregression model

In this subsection, we briefly describe the main empirical framework used in this analysis. We employ a standard VAR model to estimate the responses of the variables capturing income and wealth inequality to the uncertainty shock while accounting for their dynamic relationship with other aggregate variables. The baseline VAR model includes (i) standard macroeconomic and financial variables characterizing the U.S. economy common to each VAR model, (ii) each of the different uncertainty measures (financial vs. macroeconomic), and (iii) various inequality metrics entering the VAR system in turn. Except for the last part of the VAR system (i.e., inequality metrics), our empirical model is similar to that in seminal papers estimating the aggregate effect of uncertainty shocks, such as Bloom (2009) and Baker et al. (2016).

The following general representation summarizes the structural VARs used in this study:

$$Ay_t = c + \sum_{k=1}^{p} F_k y_{t-k} + u_t, \tag{3}$$

where y_t is an $n \times 1$ vector of the aforementioned variables ($n = 6$ in the baseline model). c denotes an $n \times 1$ vector of constants and linear time trends. F_k are $n \times n$ matrices of coefficients, and u_t is an $n \times 1$ vector of structural shocks. The lag p for the analysis is 12, which is much more conservative than what the Akaike and Bayesian information criteria suggest (between two and six lags). Following much of the literature, we identify the simultaneous relations of structural shocks by assuming that A is a lower triangular matrix (i.e., recursive identification):

$$A = \begin{pmatrix} 1 & 0 & \dots & 0 \\ a_{21} & 1 & \dots & 0 \\ \dots & \dots & \dots & 0 \\ a_{n1} & \dots & a_{nn-1} & 1 \end{pmatrix}.$$

A reduced-form model can be obtained from (1):

$$y_t = A^{-1}c + \sum_{k=1}^{p} B_k y_{t-k} + A^{-1}\Sigma\epsilon_t, \qquad \epsilon_t \sim N(0, I_n), \tag{4}$$

where $B_k = A^{-1}F_k$ for $k = 1, 2, \dots, p$, and

$$\Sigma = \begin{pmatrix} \sigma_1 & 0 & \dots & 0 \\ 0 & \sigma_2 & \dots & 0 \\ \dots & \dots & \dots & 0 \\ 0 & \dots & 0 & \sigma_n \end{pmatrix},$$

where σ_i denotes the standard deviation of each structural shock. Recursive identification in our six-variable VAR model is achieved by the following Cholesky ordering: the log of industrial production, log of CPI, federal funds rate (with the Wu–Xia shadow rate), log of S&P500, uncertainty index, and inequality measure. The ordering of the variables closely follows that of Jurado et al. (2015) and indicates that uncertainty shocks do not have a contemporaneous effect on other aggregate variables, whereas shocks to other aggregate variables can affect uncertainty contemporaneously. Because we are interested only in identifying one shock (i.e., the uncertainty shock), the ordering among variables placed before the uncertainty measure is irrelevant.

Following Baker et al. (2016), the VAR system includes all variables in levels, rather than in first differences. A large body of literature on this issue suggests that estimating a VAR model in levels is still desirable to preserve the co-integrating relationships among variables (Sims et al., 1990). Moreover, Bachmann et al. (2013) criticized the HP filtering used in Bloom (2009) for artificially removing the potential medium-term dynamics of uncertainty shocks, which could be relevant for inequality dynamics.

III. EMPIRICAL FINDINGS

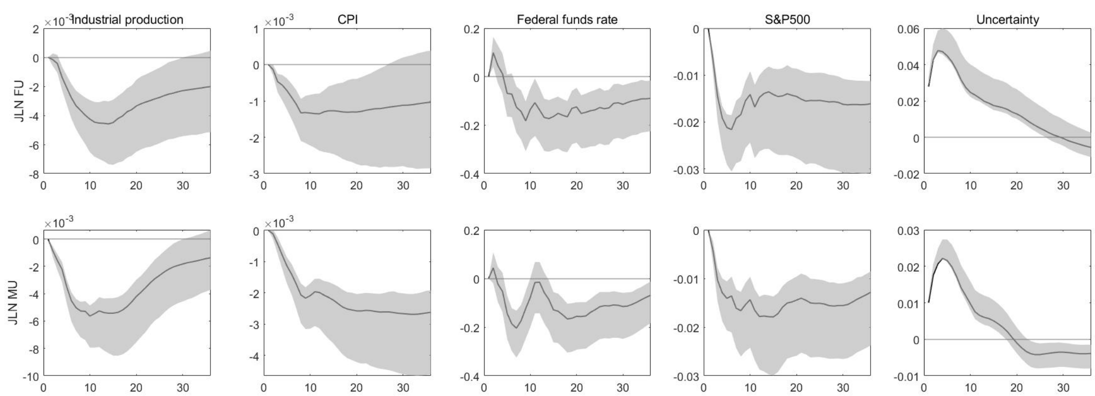
A. Main results

Response of aggregate variables. As a first pass, we check whether the main findings in the literature still hold in our main specification and sample period. To do so, we examine the responses of the aggregate variables to each of the two types of uncertainty shocks (Figure 3). As a measure of inequality, we always use the relative income share of the top 10% to fix the model, but we do not report the response of this variable here.[8] Figure 3 confirms the well-known adverse effect of uncertainty shocks on output, which holds for both the uncertainty measures. After one year, a one-

[8] We also confirm that the response of aggregate variables to the uncertainty shock does not depend on the choice of the income group to be included by replacing the top 10% income share sequentially with other groups.

standard-deviation uncertainty shock reduces output by 0.5%, similar to earlier studies on the U.S. economy. Consistent with Leduc and Liu (2016) and Basu and Bundick (2017), we observe a significant decline in CPI in response to the uncertainty shock, suggesting that uncertainty shocks act as a negative aggregate demand shock. In response to declining output and inflation, the Federal Reserve actively lowers the short-term policy rate. Finally, risky asset prices, such as stock prices, decrease sharply following uncertainty shocks, thereby tightening financial market conditions.

Figure 3. The response of aggregate variables to uncertainty shocks



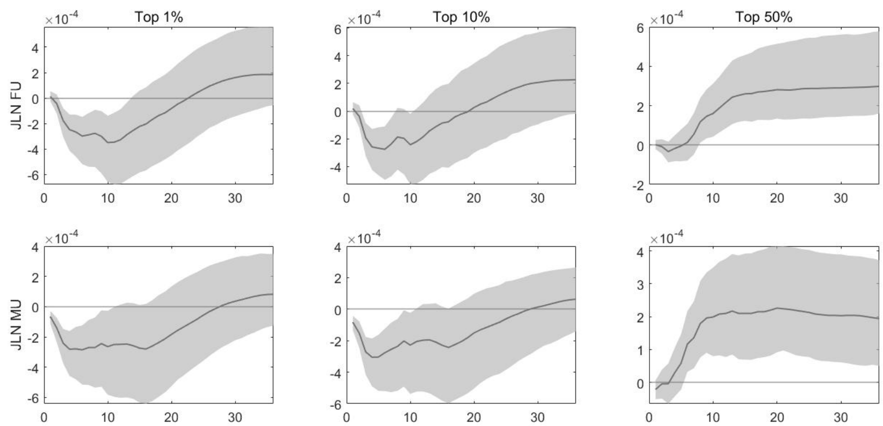
Note: This graph plots the 36-month-horizon impulse response functions of the aggregate variables to one standard deviation uncertainty shock. The income share of the top 10% is used as a measure of inequality, but the result is not presented in the figure. The shaded area represents the bootstrap 90% confidence interval. Each row represents different uncertainty measures and each column represents the responses of different macroeconomic variables. The sample period is January 1976 to December 2019.

Response of income inequality. After confirming that the aggregate effects of uncertainty shocks are similar across their measures and consistent with previous studies, we provide the main finding of the paper: the distributional consequence of uncertainty shocks. Since the database of Blanchet et al. (2022) does not allow for the construction of the Gini index, which is the most popular measure of inequality, we plot the response of the income share of the top 1%, 10%, and 50% in Figure 4 to facilitate a comparison with most studies that treat a single statistic as a measure of inequality.

The top 1% and 10% income shares decline after uncertainty shocks, suggesting that uncertainty shocks reduce inequality in the upper-income distribution, regardless of their origin.

However, the top 50% of the income share persistently increases following the uncertainty shock, suggesting that uncertainty shocks increase inequality in the lower income distribution. Thus, our finding complements that of Fischer et al. (2021) that nationwide uncertainty shocks reduce the income Gini coefficients of most U.S. regions but that the conclusion depends on whether we focus on the upper or lower income distribution.

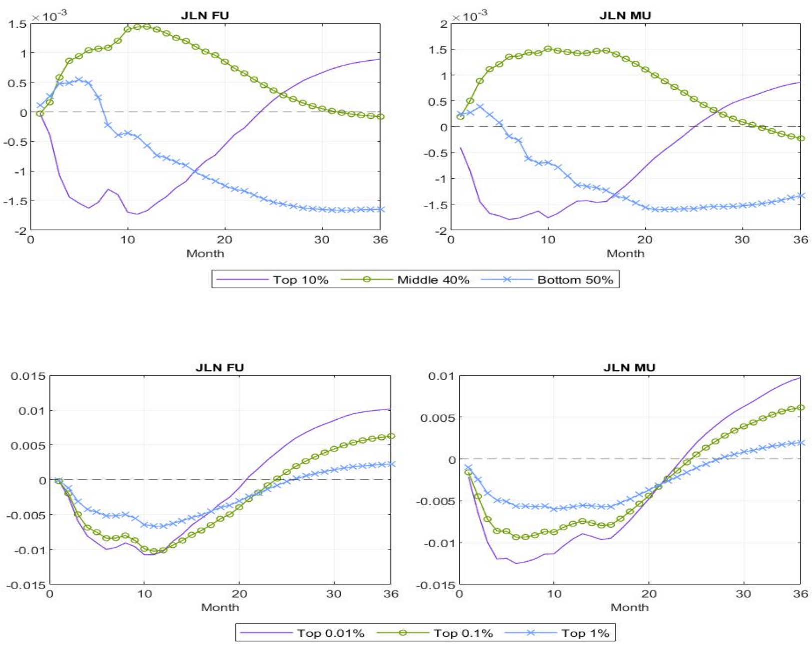
Figure 4. The response of income share to uncertainty shocks



Note: This graph plots the 36-month-horizon impulse response functions of various income shares to one standard deviation uncertainty shock. The shaded area represents the bootstrap 90% confidence interval. Each row represents different uncertainty measures and each column represents the response of the income shares of the different groups. The sample period is January 1976 to December 2019.

Given the different distributional implications of the uncertainty shocks documented above depending on the exact measure of inequality, we consider the relative income growth of every income group for a comprehensive understanding. To effectively summarize the differential responses of different income groups, we report only the response of relative income growth in Figure 5 for both measures of uncertainty. In the top panel, we report the responses for the top 10%, middle 40%, and bottom 50%. In the bottom panel, we focus on the response of the top income distribution by presenting the responses for the top 0.01%, 0.1%, and 1%. Demonstrating the income response of this far-right-tail group to uncertainty shocks is another important contribution of this study.

Figure 5. The response of relative income growth to uncertainty shocks



Note: This graph plots the 36-month-horizon impulse response functions of relative income growth to one standard deviation uncertainty shock. Each column represents a different uncertainty measure. The first row represents the responses of the relative income growth of the top 10%, middle 40%, and bottom 50%. The second row represents the responses of the relative income growth in the top 0.01%, 0.1%, and 1%. The sample period is January 1976 to December 2019.

The qualitative pattern of responses is quite similar across both measures of uncertainty: regardless of source, uncertainty shocks have particularly detrimental effects on the income of the rich (top 10% or above). The poor (bottom 50%) were also more adversely affected. A decline in the nominal interest rate can explain the adverse effect on the rich via the income composition channel, whereas the slowdown in economic activity and rising unemployment can explain why the poor group is negatively affected by the earnings heterogeneity channel.[9] The middle class (middle 40%) tends to perform better, which is in contrast to Theophilopoulou (2021), who found that the middle class in the United Kingdom is more adversely affected by uncertainty shocks than the

[9] According to the income composition channel, high-income households rely more on business and capital income, resulting in a decline in interest income after the uncertainty shock. In contrast, low-income households mainly rely on labor income and their employment status is most vulnerable to economic contractions induced by the uncertainty shock.

poor.[10] This difference can be explained by the inflationary effects of uncertainty shocks in the U.K. economy. To the extent that unexpected inflation arbitrarily favors borrowers at the expense of lenders, inflationary uncertainty shocks in the United Kingdom are particularly damaging to the middle class, who are more likely, than the poor, to be savers. Likewise, deflationary uncertainty shocks in the United States are particularly damaging to the poor.

Among the rich, the richer groups tend to suffer more from uncertainty shock, which has not been documented in previous studies. For example, the adverse effect on the super-rich (top 0.01%) is an order of magnitude larger than that on the rich (top 10%). Since the labor market participation of the super-rich is largely irrelevant to their income, such a large effect is likely driven by a sharp decline in capital income and business income following the slowdown in economic activity. Although we do not report the confidence intervals for the sake of efficient presentation of the results, the impulse response functions were estimated precisely. Figure A.1 in the Appendix plots the response of each income group separately, together with their 90% bootstrapped confidence intervals.

We then evaluate the contribution of uncertainty shocks to the income inequality dynamics by conducting a forecast error variance decomposition of the relative income growth across different groups. The top panel in Table 2 reports the share of error variance in the relative income growth explained by each type of uncertainty shock over the three forecasting horizons (12, 24, and 36 months after the shock). Overall, uncertainty shocks explain a non-trivial share of the variation in relative income growth, especially for the middle 40%. Our finding on the importance of uncertainty shocks as a driver of inequality is comparable to that of the study conducted in the United Kingdom

[10] Unlike the U.S. economy analyzed here, uncertainty shocks in the U.K. economy are followed by an increase in inflation. See Mumtaz and Theodoridis (2018) and Choi and Yoon (2022), who document that uncertainty shocks could be seen as a negative aggregate supply shock in the United States before the Great Moderation. Accounting for heterogeneous inflationary effects of uncertainty shocks between the two countries is beyond the scope of this paper, but is discussed in Choi (2017).

by Theophilopoulou (2021).[11] Given the conservative recursive identification assumption made regarding the uncertainty variable, we conclude that uncertainty shocks are a non-negligible driver of income inequality over business cycles.[12]

Table 2. The role of uncertainty shocks in explaining inequality

		JLN financial			JLN macro		
		H=12	H=24	H=36	H=12	H=24	H=36
Income	Top 0.01%	2.26%	1.41%	2.00%	3.46%	2.32%	2.46%
	Top 0.1%	4.03%	3.19%	3.39%	4.33%	3.33%	3.44%
	Top 1%	6.32%	6.11%	5.94%	11.16%	14.29%	15.37%
	Top 10%	5.44%	4.64%	4.89%	6.85%	5.98%	5.95%
	Middle 40%	9.04%	10.23%	9.32%	12.60%	14.69%	13.21%
	Bottom 50%	0.60%	2.67%	6.30%	1.02%	4.37%	7.26%
		H=12	H=24	H=36	H=12	H=24	H=36
Wealth	Top 0.01%	9.98%	15.38%	17.94%	8.31%	12.98%	12.81%
	Top 0.1%	10.67%	17.12%	19.58%	8.47%	13.81%	13.71%
	Top 1%	8.10%	14.73%	17.29%	7.07%	13.40%	13.87%
	Top 10%	0.36%	0.33%	0.98%	0.23%	0.31%	0.99%
	Middle 40%	3.51%	3.57%	3.57%	2.03%	4.22%	3.89%
	Bottom 50%	0.99%	2.03%	4.57%	1.94%	4.20%	3.40%

Note: The top panel of the table shows the forecast error variance decomposition of the relative income growth explained by uncertainty shocks over the three forecasting horizons. (H=12, 24, and 36 months). The bottom panel of the table shows the forecast error variance decomposition of relative wealth growth explained by uncertainty shocks over the three forecasting horizons (H=12, 24, and 36 months). The sample period is January 1976 to December 2019.

Uncertainty and redistribution policy. To shed light on the ultimate effect of uncertainty shocks on inequality, we repeat the previous exercise by using disposable income instead of the factor income considered in the baseline analysis. According to the income composition channel, low-income

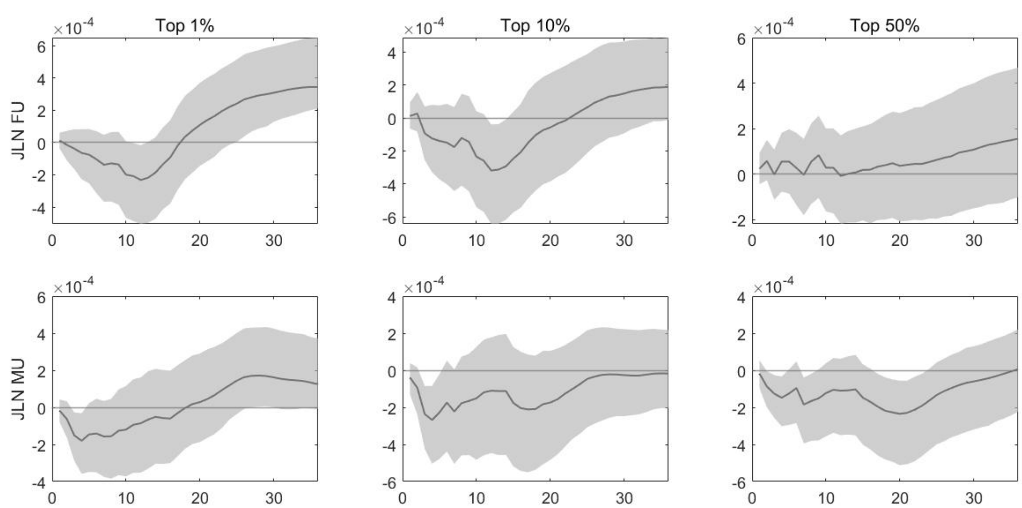
[11] Using the same identifying assumption and a similarly constructed uncertainty measure, Theophilopoulou (2021) finds that uncertainty shocks explain about 10% of the variation in the income Gini cofficient for the U.K. economy.

[12] For example, if we treat uncertainty as the most exogenous variable in the VAR system by placing it before other variables, the share of variation explained by the uncertainty shock tends to further increase. After 12 months, JLN financial uncertainty (JLN macro uncertainty) shocks explain 7.16 (10.92)%, 11.89 (19.56)%, 0.76 (1.42)% of relative income growth for the top 10%, middle 40%, and the bottom 50%, respectively.

households rely more on transfers, suggesting that the narrative of income inequality can change if the role of redistribution policy is considered.

As Figure 6 shows, the implication of the uncertainty shock on the income share of the rich remains similar. However, the response of the top 50% becomes statistically insignificant for financial uncertainty and even negative for macroeconomic uncertainty. This finding suggests that, in response to an exogenous increase in uncertainty, the redistribution policy transfers income to the poor, reducing inequality at both the upper and lower ends of the distribution, regardless of its measure. Once the redistribution policy is considered, we conclude that uncertainty shocks do not increase income inequality despite the theoretical appeal of the mechanism. Moreover, to the extent that consumption depends on disposable income than market income, our finding provides a rationale for the main finding of De Giorgi and Gambetti (2017) that uncertainty shocks reduce U.S. consumption inequality.

Figure 6. The response of disposable income share to uncertainty shocks



Note: This graph plots the 36-month-horizon impulse response functions of disposable income shares to the one standard deviation uncertainty shock. The shaded areas represent the bootstrap 90% confidence interval. Each row represents different uncertainty measures and each column represents the response of the income share of the different groups. The sample period is January 1976 to December 2019.

Response of wealth inequality. We focus on wealth inequality by estimating the same VAR models but replacing the income share with the wealth share of different groups. This exercise is particularly important because most existing studies on inequality have been limited to income or consumption inequality due to the lack of high-frequency disaggregated wealth data. As shown in Figure 1, the concentration on the rich is much more severe for wealth than for income. Indeed, the wealth holding of the bottom 50% is close to zero or even negative (i.e., debts are larger than assets).

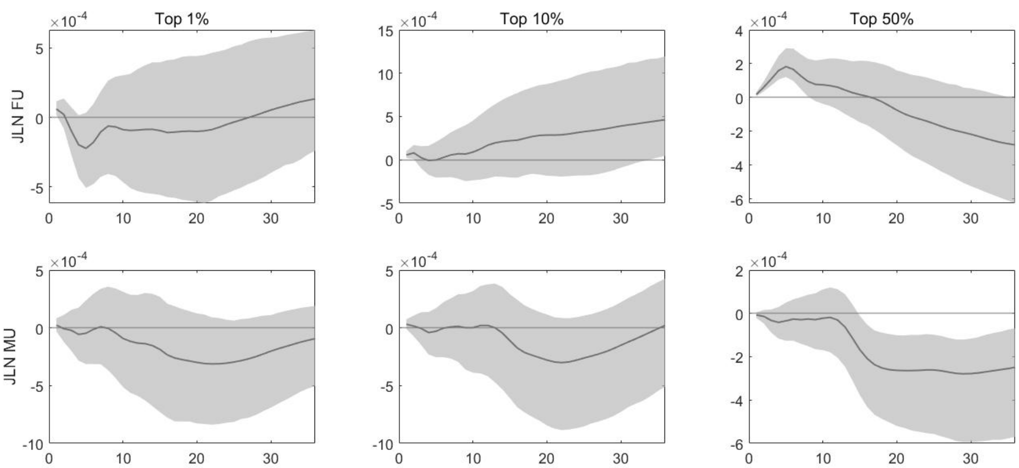
Although wealth is essentially a cumulation of income over time, there are many reasons to expect that the effect of uncertainty shocks on wealth distribution differs from that on income distribution. The most obvious factor driving the difference is the larger share of the financial wealth of the rich, which is heavily influenced by the financial market conditions and monetary policy. To the extent that risky asset prices increase in response to monetary easing, the highest benefits are for the financial wealth of the rich (i.e., the portfolio composition channel), which is distinct from a decline in interest income via the income composition channel. For example, Mumtaz and Theophilopoulou (2017) find that expansionary monetary policy shocks reduce income and consumption inequality, whereas Mumtaz and Theophilopoulou (2020) document that they increase wealth inequality in the United Kingdom.[13] Thus, it would be interesting to study whether uncertainty shocks have different implications for wealth and income distributions.

Figure 7 reports the main results: the response of the wealth share of the top 1%, 10%, and 50%. Unlike the income share responses, however, the wealth share responses of the top 1% and top 10% are statistically insignificant, reflecting a smaller time-series variation in the wealth share reported in Figure 1. Interestingly, the response of the top 50% wealth share is different from that of the top 50% income share. Although the top 50% income share increases significantly after both types of uncertainty shocks, the top 50% wealth share tends to decrease after the same shocks

[13] This conclusion is subject to a caveat because the sample on wealth inequality (2006–2018) is much shorter than income inequality (1969–2012) and they barely overlap. In contrast, our study is based on a common sample, allowing for direct comparison.

(except for a short-run increase after financial uncertainty shock). Thus, uncertainty shocks do not have the same implication on wealth distribution and income distribution, which warrants further investigation.

Figure 7. The response of wealth share to uncertainty shocks

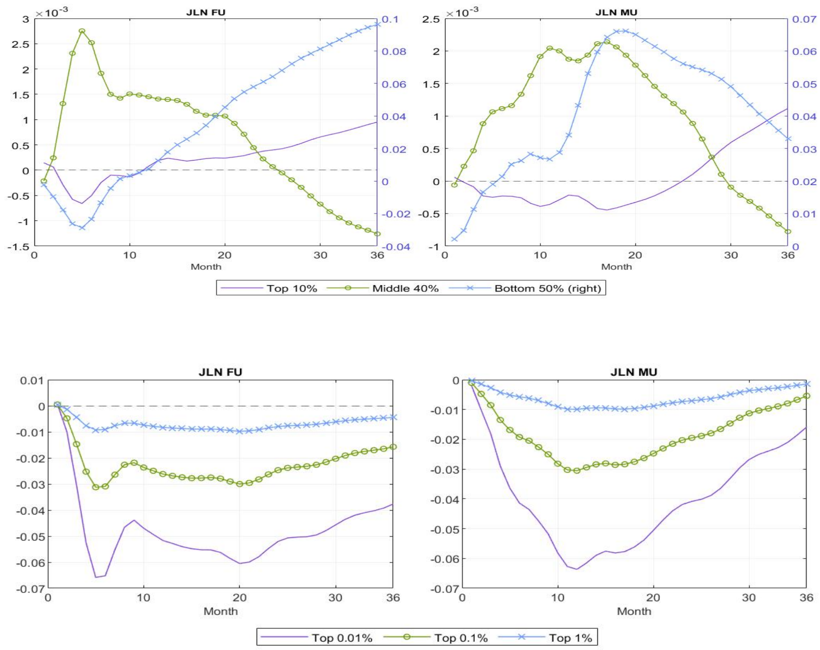


Note: This graph plots the 36-month-horizon impulse response functions of wealth shares to one standard deviation uncertainty shock. The shaded area represents the bootstrap 90% confidence interval. Each row represents different uncertainty measures and each column represents the response of the wealth share of the different groups. The sample period is January 1976 to December 2019.

To fully characterize the effect of uncertainty shocks on the wealth distribution, Figure 8 plots the response of relative wealth growth to uncertainty shocks for each group.[14] Because the response of the bottom 50% dwarfs that of the top 10% and middle 40% (higher sensitivity of the bottom 50%'s wealth due to the low level shown in Figure 1), we plot its response on the different axis. Although the inference on the top 10% and middle 40% is largely similar to the income response, the response of the bottom 50% wealth growth is different.

[14] See Figure A.2 in the Appendix for the individual response with the 90% confidence interval.

Figure 8. The response of relative wealth growth to uncertainty shocks



Note: This graph plots the 36-month-horizon impulse response functions of relative wealth growth to the one standard deviation uncertainty shock. Each column represents a different uncertainty measure. The first row represents the responses of the relative wealth growth of the top 10%, middle 40%, and bottom 50%. The second row represents the responses of the relative wealth growth in the top 0.01%, 0.1%, and 1%. The sample period is January 1976 to December 2019.

Except for the short-run decline following the financial uncertainty shock, relative wealth growth at the bottom 50% switches to positive, and this effect is an order of magnitude larger than the growth of other groups, suggesting that low-wealth households disproportionally benefit from uncertainty shocks. The portfolio rebalancing mechanism in the two-asset structure of Bayer et al. (2019) can explain why the wealth-rich are more negatively affected by uncertainty shocks than the wealth-poor.

Bayer et al. (2019) document that households differ substantially in the share of their liquid assets and that wealth-rich households hold a greater share of illiquid physical capital with higher returns than liquid assets during normal times. However, when household income uncertainty increases, the price of and return on capital fall more than the return on liquid assets, suggesting that wealth-rich households lose the most as capital returns fall strongly in times of high uncertainty.[15] Wealth-poor households holding (relatively) more liquid assets, by contrast, even though they hold less total wealth, are much better insured and do not suffer as much from lower capital returns.

An increase in personal transfers (redistribution policy) following uncertainty shocks (shown in Figure 9) can also account for such a large response given the near-zero (or even negative) wealth of the bottom 50%, as shown in Figure 1. Similar to the income response, among the rich, the wealthier group is more adversely affected by the uncertainty shock, likely due to the disproportionately large financial asset holdings of this group (Bach et al., 2020; Hubmer et al., 2021).

In parallel with income inequality, we conduct a forecast error variance decomposition of the relative wealth growth explained by the uncertainty shock in the bottom panel of Table 2. Compared to income inequality, the role of both types of uncertainty shocks has decreased, especially for the top 10% and middle 40%, reflecting the difference between the flow and stock variables and the short-run nature of high-frequency uncertainty shocks. However, uncertainty shocks explain a much larger share of the relative wealth growth of the super-rich (the top 1% and above) than income growth, which is consistent with the significant effect of uncertainty shocks on risky asset markets such as the stock market, where the majority of the super-rich's wealth is allocated.

B. Robustness checks

Alternative measures of uncertainty. We present the responses to alternative measures of uncertainty (the VIX and EPU indices) in Figure A.1 (income) and A.2 (wealth) in the Appendix. The results for income inequality are the same for these alternatives, except that the response of

[15] The correlation between the estimated household income risk in Bayer et al. (2019) and our measures of uncertainty is 0.42 for financial uncertainty and 0.41 for macroeconomic uncertainty, suggesting that their uncertainty measure largely captures both dimensions of uncertainty.

relative income growth becomes less persistent, a finding consistent with that of Jurado et al. (2015) for aggregate variables. For wealth inequality, using alternative uncertainty measures delivers qualitatively similar results for all groups except for the top 10%.

Alternative VAR specifications. We further checked the robustness of our findings by employing (i) the alternative ordering of the variables, matching Bloom (2009) and (ii) the generalized impulse response functions (IRFs) developed by Koop et al. (1996) that the responses are invariant to any reordering of the variables in the VAR system. For the former, the uncertainty variable is placed second in the VAR system, after the stock market variable. This recursive ordering implies that uncertainty is exogenous to a macroeconomy. Given the contrasting evidence regarding the exogeneity of uncertainty (Fajgelbaum et al., 2017; Ludvigson et al., 2021), we use both types of identifying assumptions to draw a balanced conclusion.[16] For the latter, the generalized IRFs do not impose orthogonality, allowing for meaningful interpretation of the initial impact response of each variable to shocks to any other variable

Figures A.3 and A.4 in the Appendix report the results that confirm that the ordering of the uncertainty variable is largely irrelevant to its distributional consequences. This is not surprising because our main focus is not the response of an aggregate variable, but rather the response of a disaggregated variable (i.e., inequality metric), which is less likely subject to the concern of reverse causality. In other words, while rising uncertainty could be an endogenous response to macroeconomic development, it is difficult to imagine that changes in the income or wealth of a particular group drive uncertainty about the U.S. economy.

Correlated uncertainty measures. We have included each measure of uncertainty, in turn, to investigate whether the distributional consequences of uncertainty shocks depend on their sources. However, given the strong correlation between financial and macroeconomic uncertainty measures

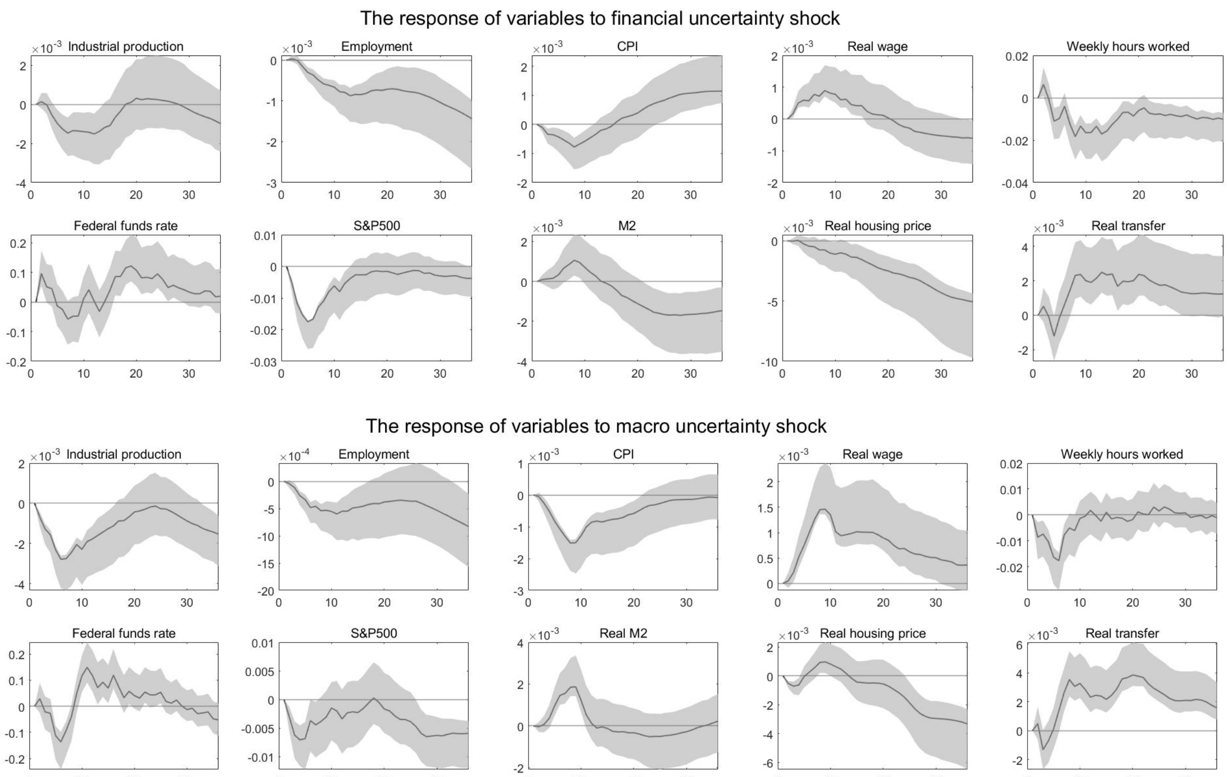
[16] The literature has debated whether rising uncertainty is an exogenous driver of business cycles or an endogenous response to business cycles. Our benchmark identifying assumption corresponds to the latter, while the identifying assumption here corresponds to the former.

(0.58), this exercise might not be able to provide a definite answer to our question. Thus, we include both types of uncertainty measures in the VAR system. The problem is that economic theory does not provide a clear answer to relative exogeneity between the two sources of uncertainty, despite some econometric evidence in Ludvigson et al. (2021) that higher macroeconomic uncertainty is likely an endogenous response to output shocks, while financial uncertainty is a likely source of output fluctuations. To draw a robust inference, we place the financial uncertainty index after the macroeconomic uncertainty index while estimating the effect of financial uncertainty shocks, and vice versa. Figure A.5 in the Appendix confirms that the key findings still hold under this consideration.

Uncertainty at different horizons. In the baseline analysis, we used short-run measures of uncertainty by focusing on the one-month-ahead unpredictability in financial or macroeconomic time series (i.e., h=1 for $U_t^F(h)$). Despite the high empirical correlation between the uncertainty measures of different horizons, it is possible that one-year-ahead uncertainty has different effects from one-month-ahead uncertainty. For example, one-year-ahead uncertainty might capture more pervasive developments in the economy, whereas one-month-ahead uncertainty can be driven by transitory events without much material impact on the macroeconomy. Thus, we re-estimated the baseline model using alternative forecasting horizons (i.e., h=3 and h=12). Figure A.6. in the Appendix confirms that our main finding hardly changes.

Larger-scale VAR model. The six-variable baseline model that we estimated was parsimonious. Following Jurado et al. (2015), we estimate a larger-scale ten-variable VAR model to guard against any remaining concern for omitted variable bias, especially from missing labor-market-related variables. As explained by Jurado et al. (2015), this model closely follows that of Christiano et al. (2005), where dynamic relationships have been the focus of extensive macroeconomic research, and the model further includes employment, real wages, hours worked, money supply (M2), housing prices, and personal transfer receipts. The Cholesky ordering closely follows that of Jurado et al. (2015).[17]

Figure 9. The response of aggregate variables to uncertainty shocks: larger-scale VAR model



Note: This graph plots 36-month-horizon impulse response functions of macroeconomic variables to the one standard deviation uncertainty shock in a larger-scale VAR model. The Cholesky ordering is the log of industrial production, the log of employment, the log of CPI, the log of real wage, weekly hours worked, the federal funds rate (with Wu-Xia shadow rate), the log of M2, the log S&P500, the log of real housing prices, the log of real personal transfers, the uncertainty index, and top 10% income share. The shaded area is the bootstrap 90% confidence interval. The sample period is January 1976 to December 2019.

Figure 9 shows the response of aggregate variables providing a hint on the economic mechanism generating distributional consequences of uncertainty shocks. In addition to the variables included in the baseline model, we document that uncertainty shocks increase real wages, money

[17] The corresponding Cholesky ordering is the log of industrial production, the log of employment, the log of CPI, the log of real wage, weekly hours worked, the federal funds rate (with Wu-Xia shadow rate), the log of M2, the log S&P500, the log of real housing prices, the log of real personal transfers, the uncertainty index, and each inequality metric.

supply, and real personal transfers, while they decrease employment, average hours worked, and real housing prices. An increase in money supply is consistent with monetary easing by the Federal Reserve. Together with a sharp decline in employment, an increase in real wages suggests that uncertainty shocks are particularly damaging to low-wage workers who are more likely to become unemployed, and therefore explains why the income-poor is particularly vulnerable to the uncertainty shock compared to the middle class. A persistent decline in real housing prices also contributes to a decline in the wealth share of the rich. As mentioned before, transfers increase substantially after the uncertainty shock, explaining why distributional consequences of uncertainty shocks differ when using market income and disposable income. In addition, Figure A.7 in the Appendix confirms that expanding the information set of the VAR model yields largely similar results on the distributional consequences of uncertainty shocks for both income and wealth.

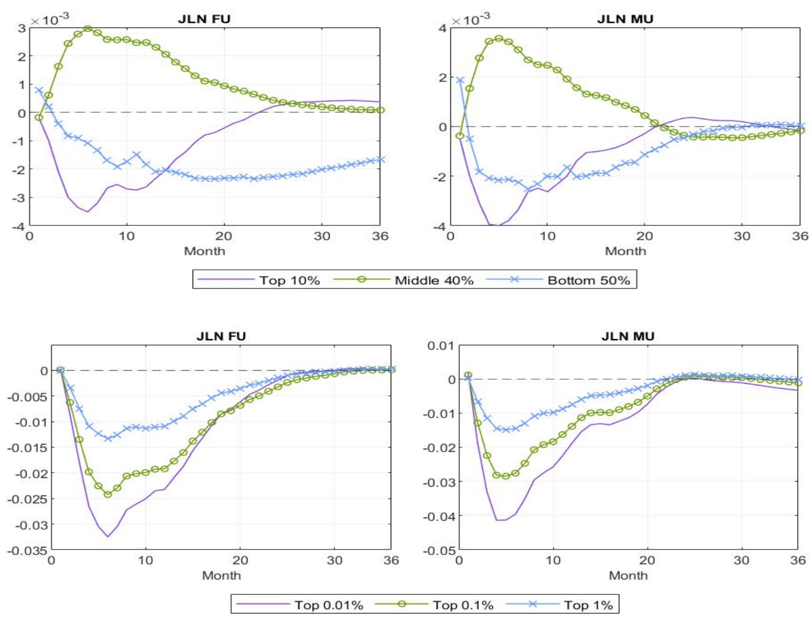
Structural break. It is well known that the U.S. economy experienced a structural break in the 1980s and many macroeconomic variables behave differently after the Volcker period (i.e., the Great Moderation). In this sense, it might not be ideal to assume parameter stability in our sample spanning both the pre and post-Volcker period. Indeed, Choi (2013) documented that the macroeconomic effect of uncertainty shocks differs between these two subperiods. Thus, we re-estimate the VAR model using the observations from 1984M1 only. As shown in Figure A.8 in the Appendix, we still obtain the same narrative about the distributional consequences of uncertainty shocks.

C. COVID-19 and inequality

As shown in Figures 1 and 2, the COVID-19 pandemic has induced an important distributional consequence. For example, Clark et al. (2021) found that income inequality decreased during the pandemic in four European countries. Together with the sharp increase in uncertainty during the pandemic (Dietrich et al., 2022), this episode provided an important variation in the data that can provide insight into the uncertainty–inequality relationship. At the same time, due to the unprecedented nature of the pandemic and subsequent policy interventions such as lockdown and social distancing, this episode might have changed the relationship under study in a significant way.

Although this period was excluded from the baseline analysis due to the erratic behavior of macroeconomic variables, we re-estimate our baseline model using additional observations since 2020. As it is not possible to estimate the pandemic period separately due to the lack of sufficient observations, we instead compared the results from this extended sample with the baseline. Given the minor share of the post-COVID observations in the total observations (2 out of 46 years), if we detect any significant changes in the estimated impulse response functions, we can interpret them as supporting evidence for the distinct role of the pandemic in shaping inequality dynamics. Figure A.9 in the Appendix confirms that the aggregate effects of both types of uncertainty shocks change minimally when additional observations are included.

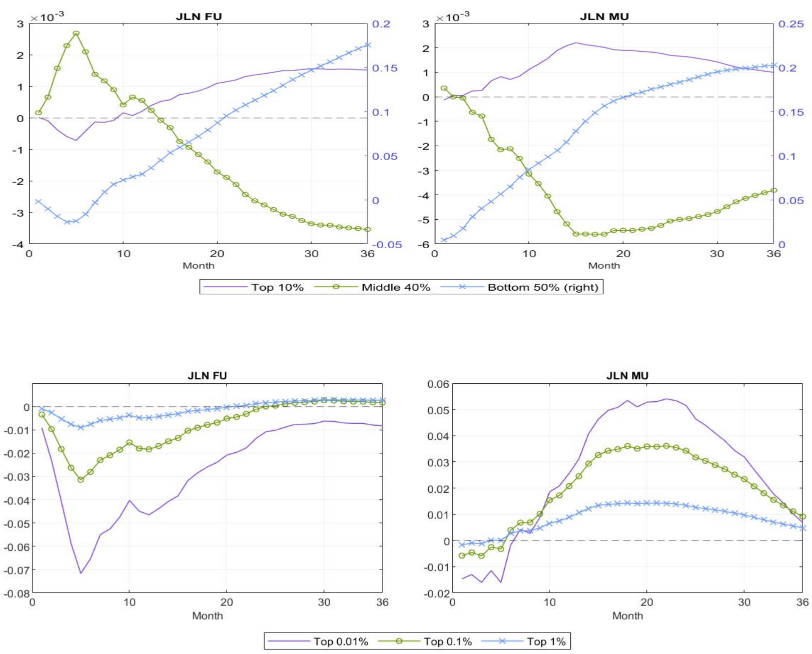
Figure 10. The response of relative income growth to uncertainty shocks (including COVID-19)



Note: This graph plots the 36-month-horizon impulse response functions of relative income growth to the one standard deviation uncertainty shock. Each column represents a different uncertainty measure. The first row represents the responses of the relative income growth of the top 10%, middle 40%, and bottom 50%. The second row represents the responses of the relative income growth of the top 0.01%, 0.1%, and 1%. The sample period is January 1976 to December 2021.

Figures 10 and 11 report the main results for income and wealth inequality, respectively. As shown in Figure 2, both financial and macroeconomic uncertainty jumped with the COVID-19 outbreak, but their forward paths were somewhat different. The inclusion of the COVID-19 episode does not alter the narrative of income inequality (the qualitative resemblance between Figures 5 and 10).[18] However, it contrasts the divergent effects of financial and macroeconomic uncertainty on wealth inequality, suggesting that Wall Street and Main Street uncertainty shocks have contrasting effects on wealth distribution. Except for the relative wealth growth of the bottom 50%, the responses of the other groups are qualitatively different between the two types of uncertainty shocks.

Figure 11. The response of relative wealth growth to uncertainty shocks (including COVID-19)



Note: This graph plots the 36-month-horizon impulse response functions of relative wealth growth to the one standard deviation uncertainty shock. Each column represents a different uncertainty measure. The first row represents the responses of the relative wealth growth of the top 10%, middle 40%, and bottom 50%. The second row represents the

[18] See Figure A.10 in the Appendix for the individual results with 90% confidence intervals.

responses of the relative wealth growth in the top 0.01%, 0.1%, and 1%. The sample period is January 1976 to December 2021.

To the extent that the rich hold most of their wealth in the form of risky assets, heightened financial uncertainty during the early phase of the pandemic was detrimental to the rich group. For example, the top 0.01% of the super-rich experienced a 7% point decline in their relative wealth growth, while the top 10% of the rich experienced a 0.1% point decrease. However, risky asset prices, such as stock prices, quickly recovered and reached a record high, driven by ultra-accommodative monetary policy. Due to monetary easing, financial uncertainty has been largely resolved despite the continuing uncertainty about the path of the macroeconomy or various policy measures combatting the pandemic.

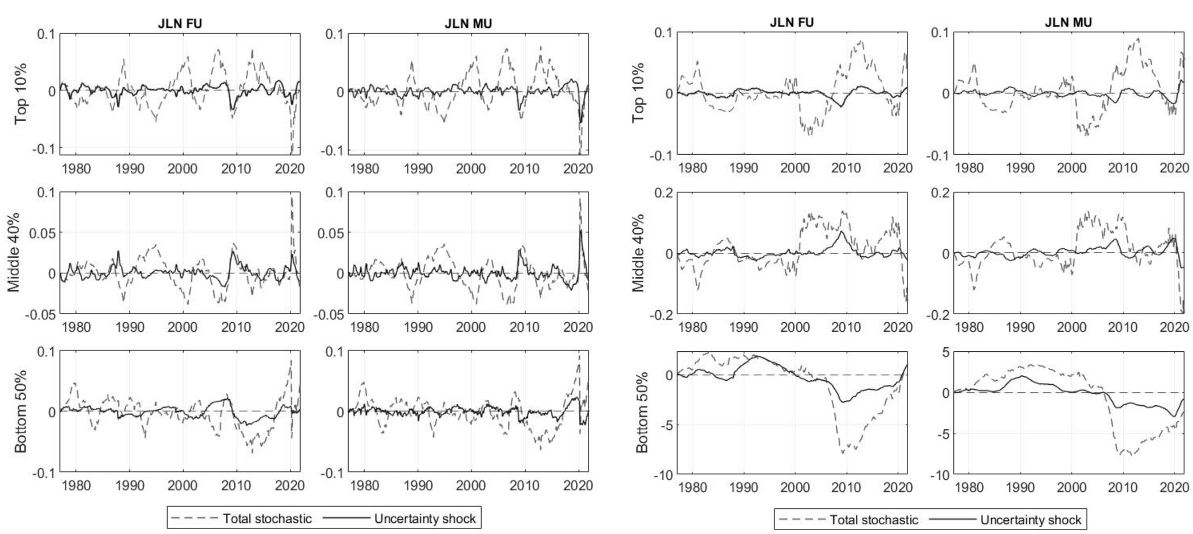
This explanation is supported by Figure A.9 in the Appendix, which shows that the decline in the stock market after the financial uncertainty shock (2%) is twice as large as that after the macroeconomic uncertainty shock (1%), although both shocks are followed by an output decline of a similar magnitude. In the unreported analysis, we find that the decline in employment is twice as large after the macroeconomic uncertainty shock (0.4%) as the financial uncertainty shock (0.2%), implying that macroeconomic uncertainty shocks become more damaging to the labor market during the pandemic. As a result, financial uncertainty tends to decrease wealth inequality, but macroeconomic uncertainty tends to increase wealth inequality once the COVID-19 period is included.[19] We take this stark difference in the response of the stock and labor markets as evidence of divergence between the Wall Street uncertainty and Main Street uncertainty documented by Pastor and Veronesi (2017), which was exacerbated during the pandemic, corroborating the findings of Altig et al. (2020).

[19] As shown in Figure A.11 in the Appendix, the distributional consequence of financial uncertainty (macroeconomic uncertainty) becomes similar to that of the VIX (EPU index) once the COVID-19 period is included, implying that the financial uncertainty index (macroeconomic index) becomes highly synchronized with the VIX (EPU index) during the pandemic.

Table A.1 summarizes the forecast error variance decomposition exercise including the COVID-19 period. Although the qualitative pattern remains similar, the role of uncertainty shocks in explaining the variation in inequality metrics has increased for relative income growth. This finding implies that the heightened uncertainty during the pandemic is an important driver of income inequality.

Historical decomposition of inequality. We perform a historical decomposition of relative income and wealth growth to determine how the role of uncertainty shocks in explaining inequality evolves, including during the recent pandemic episode. The left panel in Figure 12 presents the historical decomposition of relative income growth for each income group. On average, both financial and macroeconomic uncertainty shocks explain more of the variation in the top 10% and the middle 40% income growth than in the bottom 50%. As shown in the right panel, the share of fluctuations in relative wealth growth due to uncertainty shocks is smaller than that in relative income growth and does not present a distinct pattern over business cycles. Less pronounced cyclical fluctuations in wealth distribution can explain this finding. While the effect of uncertainty shocks is often short-lived (Bloom, 2009), the evolution of wealth (i.e., a stock variable) is much more persistent.

Figure 12. Historical decomposition of relative income (left) and wealth (right) growth



Note: This graph plots the historical decomposition of the relative income growth (left) and relative wealth growth (right). Each row represents the historical decomposition of each group. Each column represents a different uncertainty measure.

Focusing on the period surrounding the Great Recession, both shocks explain the remarkable share of relative income growth for all groups, suggesting that uncertainty shocks were indeed an important driver of inequality during this period. This finding is unsurprising, given the particular role of heightened uncertainty in shaping the Great Recession and sluggish recovery (Kose and Terrones, 2012; Bloom, 2014). However, the investigation of the pandemic has yielded mixed results. Macroeconomic uncertainty appears to play a much more important role than financial uncertainty in explaining relative income and wealth growth. The narrative from the historical decomposition exercise echoes our earlier conclusion that the distributional consequence of the pandemic for most of the population is largely driven by uncertainty about the broader economy and not financial markets that are largely a concern of the rich.

IV. CONCLUSION

Exploiting newly constructed high-frequency data on both income and wealth distribution, we present a comprehensive analysis of how different types of uncertainty shocks affect income and wealth inequality, and how the recent COVID-19 pandemic changed the documented relationship between uncertainty and inequality. We find that uncertainty shocks have heterogeneous effects on the income and wealth of different groups, which cannot be simply summarized by a single metric of inequality such as the Gini index. Thus, our findings highlight the need to assess changes in the entire distribution to avoid misleading conclusions regarding the distributional consequences of uncertainty shocks.

Contrary to many theoretical predictions, uncertainty shocks do not necessarily increase income inequality. Indeed, when disposable income is considered, they reduce income inequality, which suggests that the redistribution policy is effective in ameliorating the negative distributional consequences of uncertainty shocks. The distributional effect of uncertainty shocks on wealth is largely consistent with that of disposable income, although the effect is less precisely estimated.

However, the COVID-19 pandemic—characterized by the divergence between Wall Street and Main Street uncertainty—somewhat changes such narratives on wealth inequality, and thus deserves more scrutiny. While Wall Street uncertainty is particularly damaging to the rich, Main Street uncertainty benefits them at the expense of the middle class.

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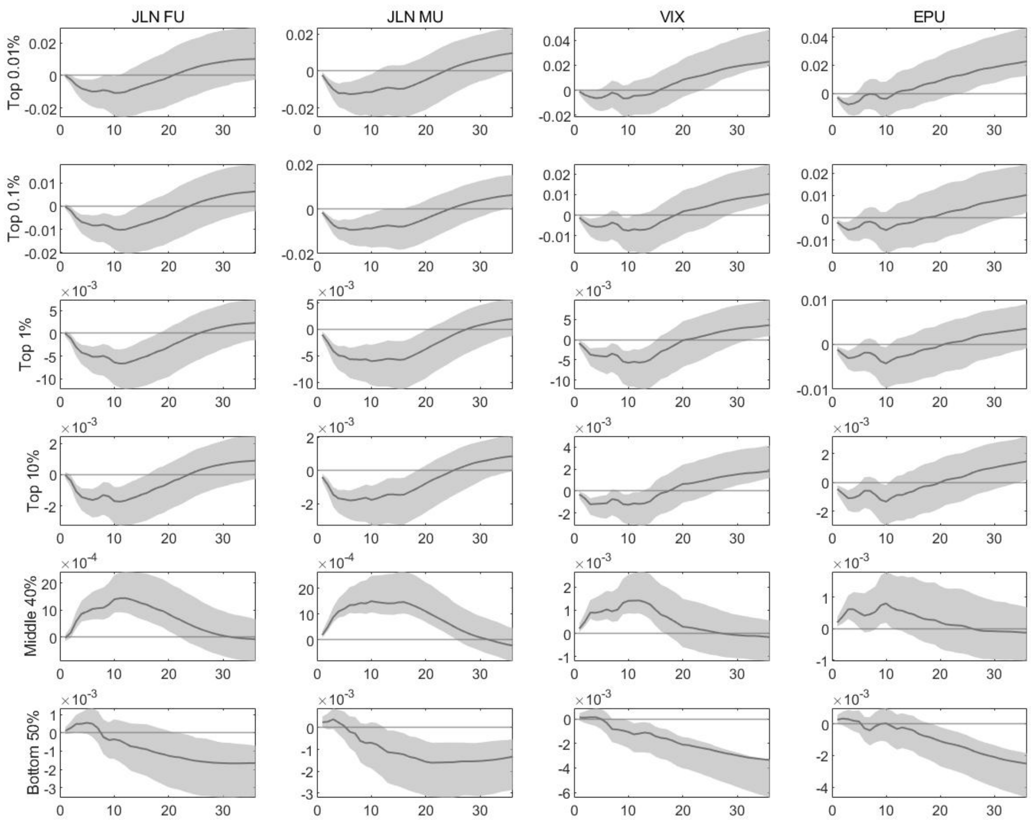
Online Appendix for "Impact of Uncertainty Shocks on Income and Wealth Inequality"

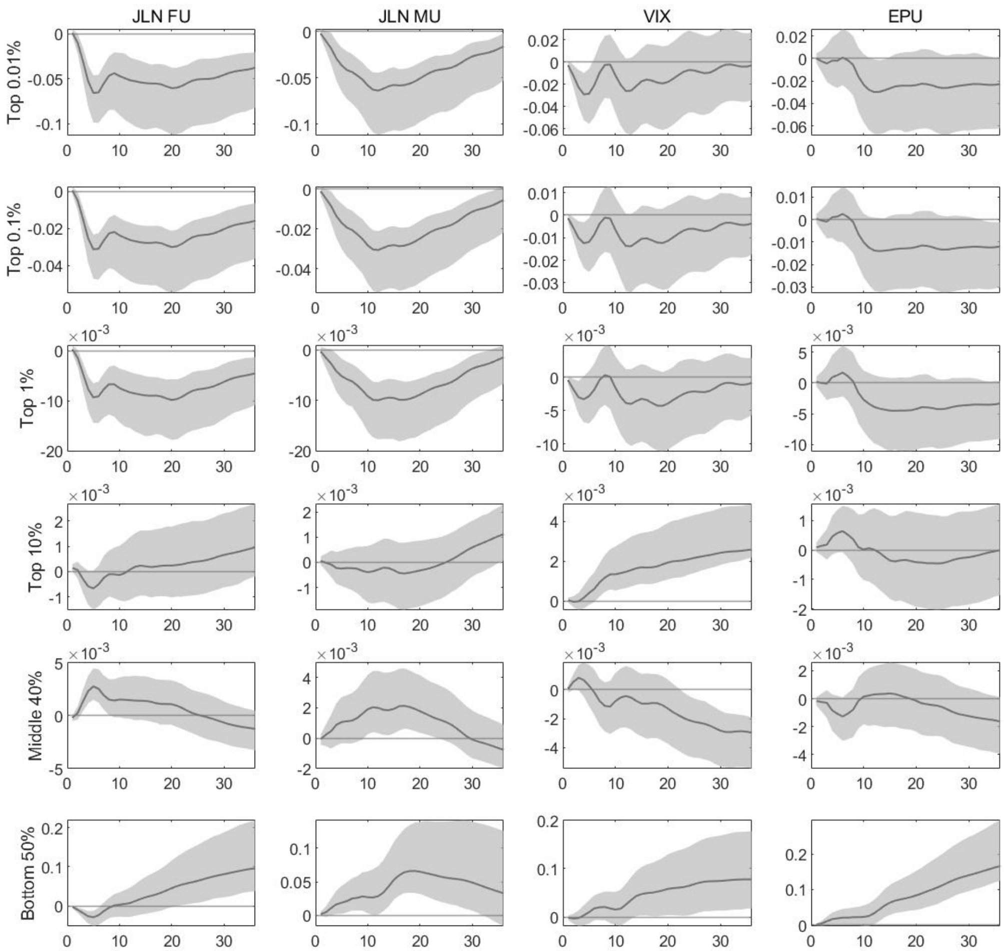
A. Additional results

Figure A.1. Response of relative income growth to uncertainty shocks



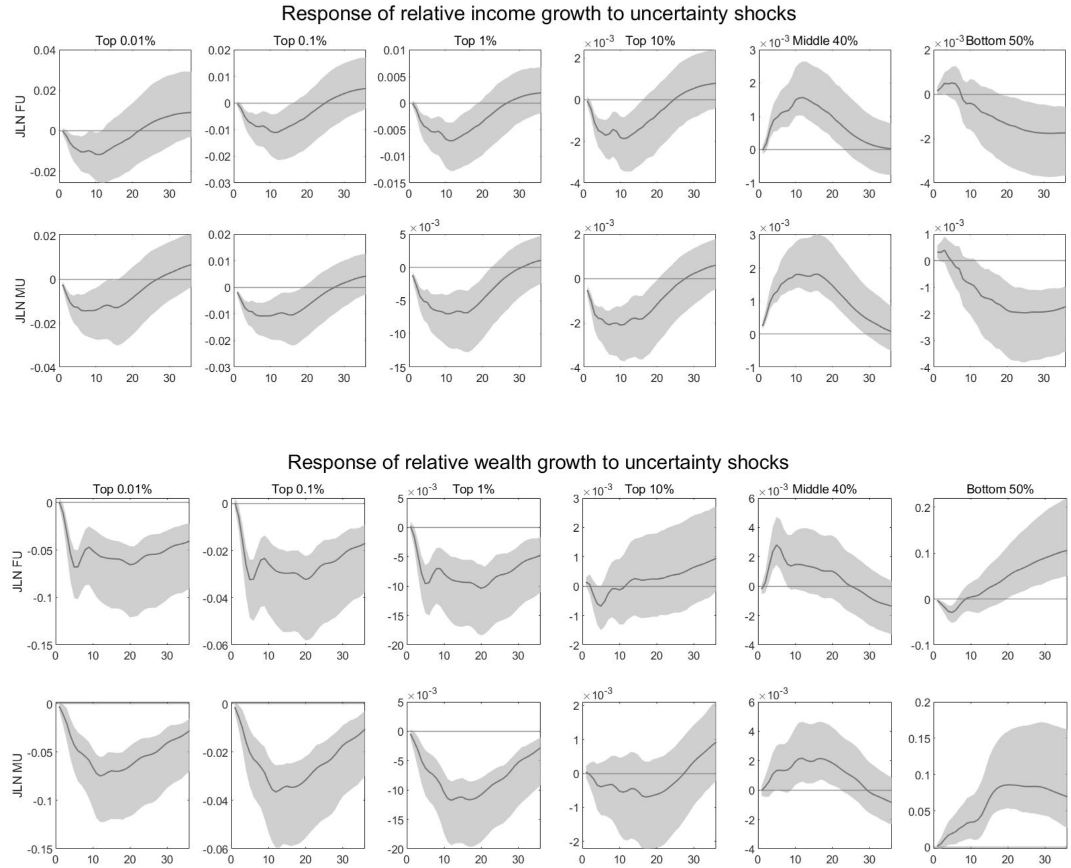
Note: This graph plots 36-month-horizon impulse response functions of relative income growths to the one standard deviation uncertainty shock. The shaded area is the bootstrap 90% confidence interval. Each column represents different uncertainty measures and each row represents the response of the relative income growth of different groups. The sample period is January 1976 to December 2019.

Figure A.2. Response of relative wealth growth to uncertainty shocks



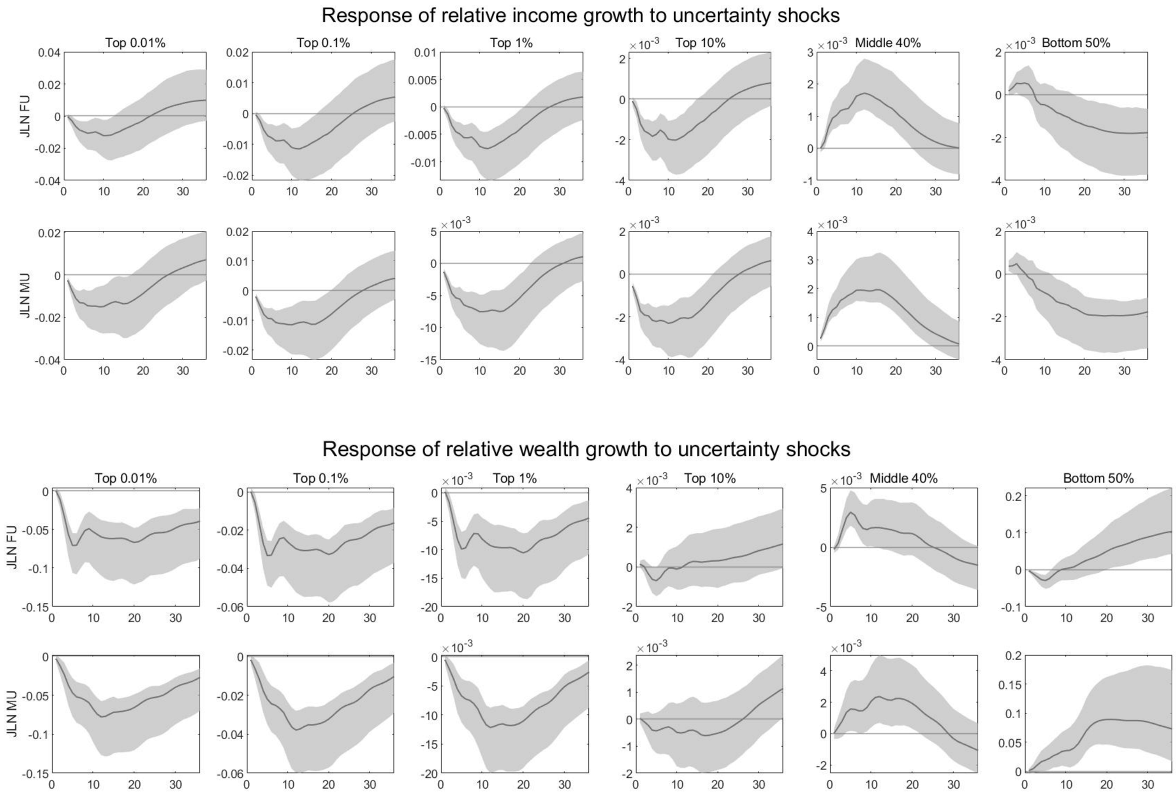
Note: This graph plots 36-month-horizon impulse response functions of relative wealth growths to the one standard deviation uncertainty shock. The shaded area is the bootstrap 90% confidence interval. Each column represents different uncertainty measures and each row represents the response of the relative wealth growth of different groups. The sample period is January 1976 to December 2019.

Figure A.3. Response of relative income (top) wealth (bottom) growth to uncertainty shocks: alternative ordering



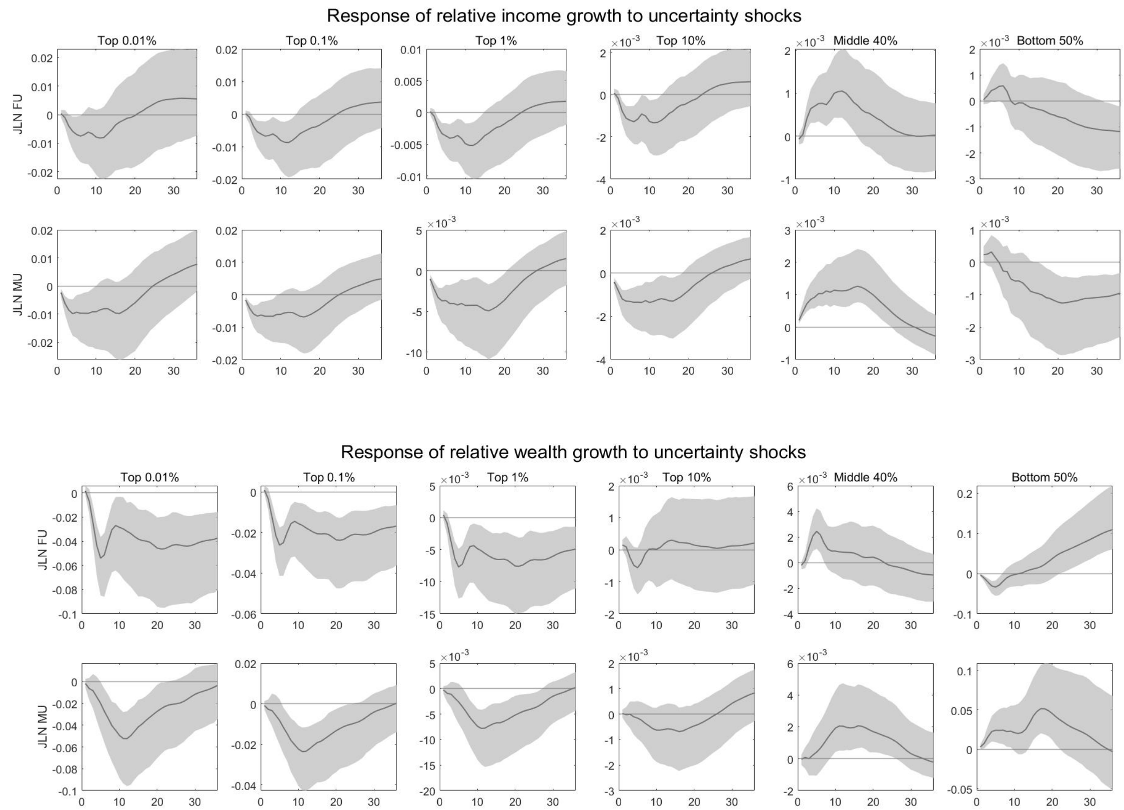
Note: This graph plots 36-month-horizon impulse response functions of relative income growth and relative wealth growth to the one standard deviation uncertainty shock. The Cholesky ordering used for these VAR models is the log of S&P500, the uncertainty index, the log of CPI, the log of industrial production, the federal funds rate, and the inequality measure. The shaded area is the bootstrap 90% confidence interval. Each row represents different uncertainty measures and each column represents a response of the income/wealth growth of different groups. The sample period is January 1976 to December 2019.

Figure A.4. Response of relative income (top) wealth (bottom) growth to uncertainty shocks: generalized IRF



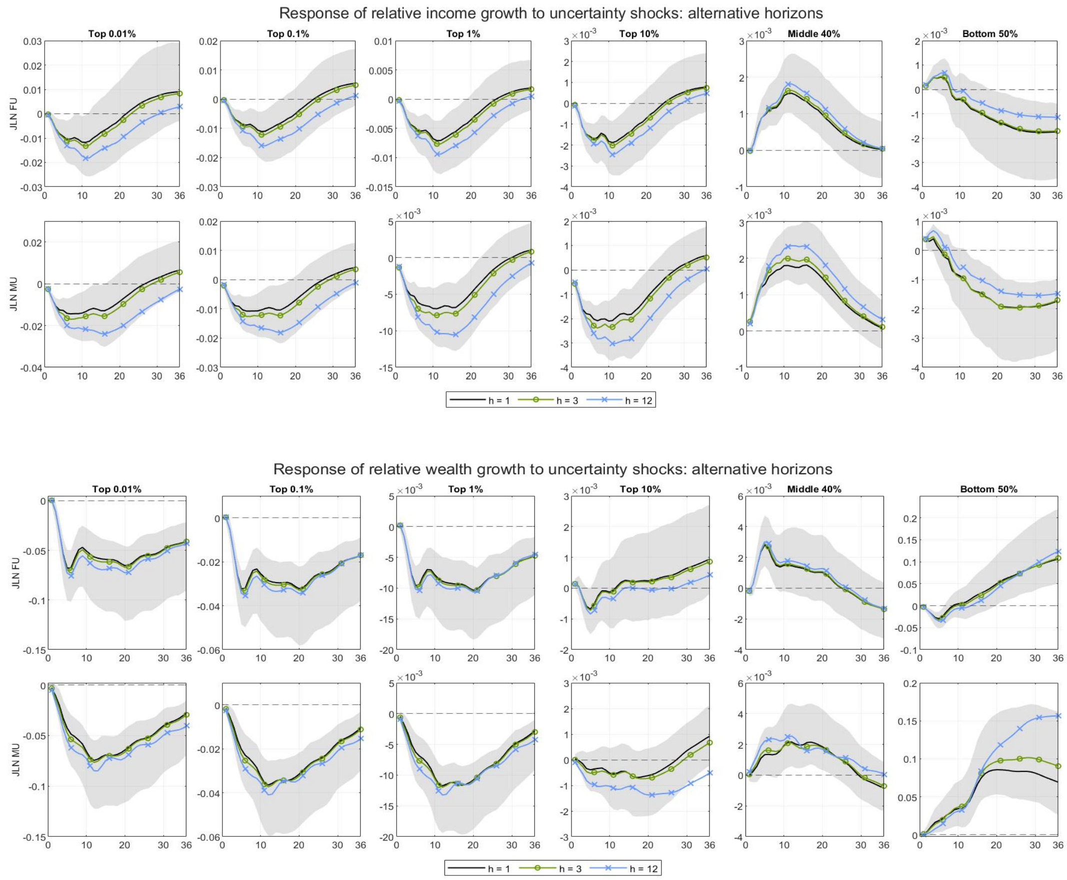
Note: This graph plots 36-month-horizon generalized impulse response functions of relative income growth and relative wealth growth to the one standard deviation uncertainty shock. The shaded area is the bootstrap 90% confidence interval. Each row represents different uncertainty measures and each column represents a response of the income/wealth growth of different groups. The sample period is January 1976 to December 2019.

Figure A.5. Response of relative income (top) wealth (bottom) growth to uncertainty shocks: correlated uncertainty



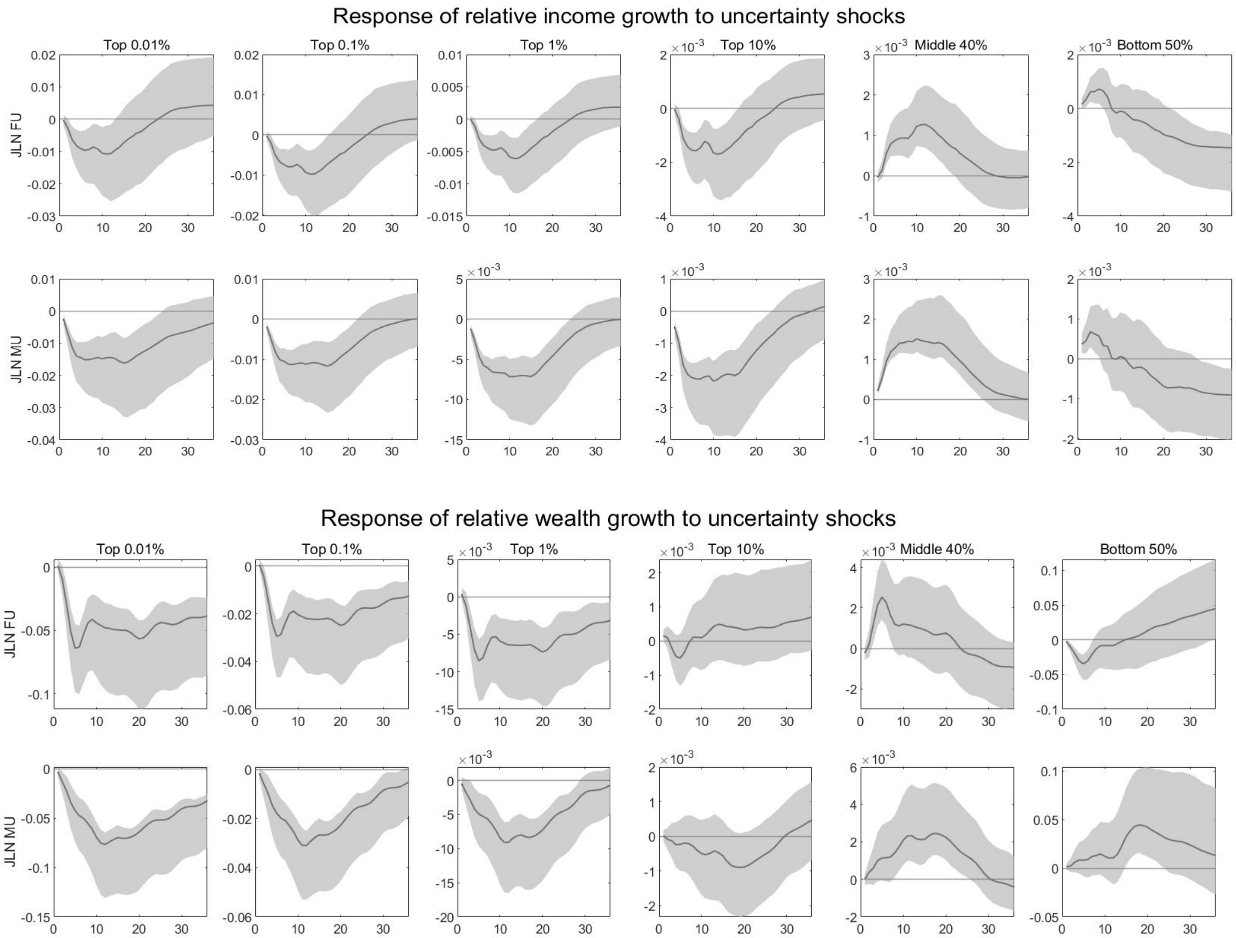
Note: This graph plots 36-month-horizon impulse response functions of relative income growth and relative wealth growth to the one standard deviation uncertainty shock. The financial uncertainty index is placed after the macroeconomic uncertainty index while estimating the effect of financial uncertainty shocks. The macroeconomic uncertainty index is placed after the financial uncertainty index while estimating the effect of macroeconomic uncertainty shocks. The shaded area is the bootstrap 90% confidence interval. Each row represents different uncertainty measures and each column represents a response of the income/wealth growth of different groups. The sample period is January 1976 to December 2019.

Figure A.6. Response of relative income (top) wealth (bottom) growth to uncertainty shocks: alternative horizons



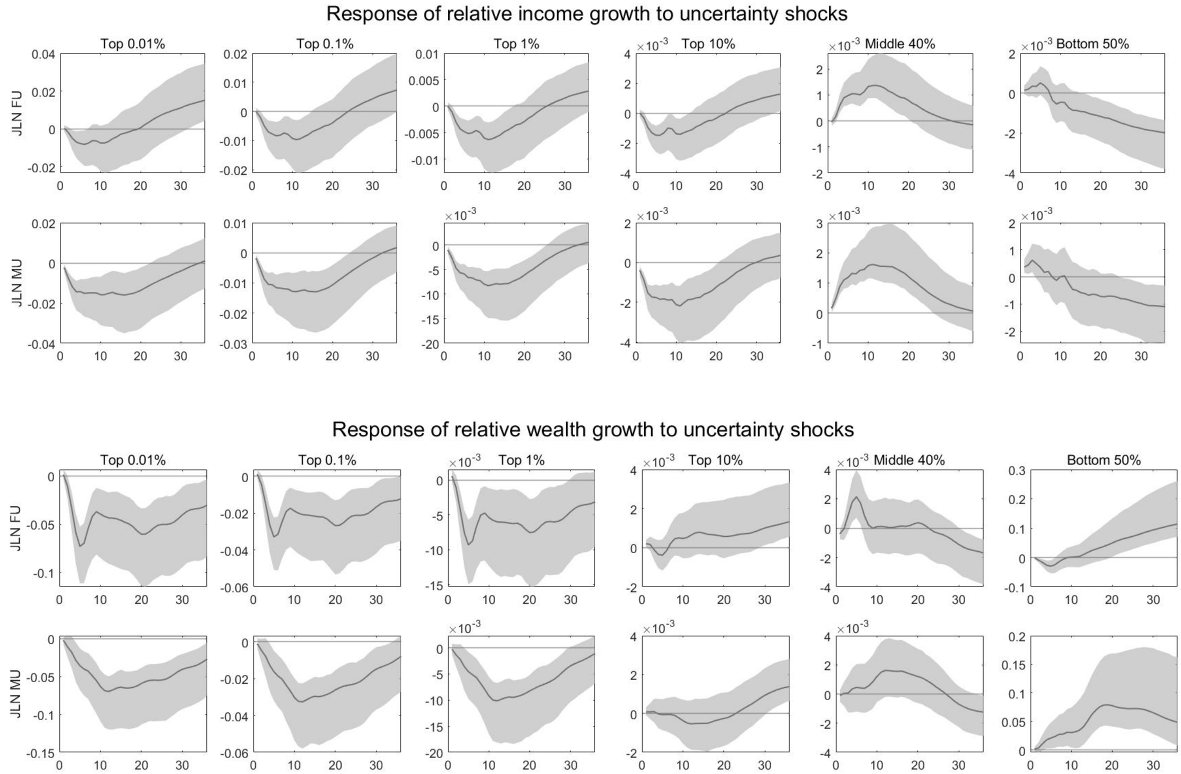
Note: This graph plots 36-month-horizon impulse response functions of relative income growth and relative wealth growth to the one standard deviation uncertainty shock. This graph additionally plots the responses of relative income/wealth growth to alternative uncertainty horizons of three and twelve months. The shaded area is the bootstrap 90% confidence interval. Each row represents different uncertainty measures and each column represents a response of the income/wealth growth of different groups. The sample period is January 1976 to December 2019.

Figure A.7. Response of relative income (top) wealth (bottom) growth to uncertainty shocks: larger-scale VAR



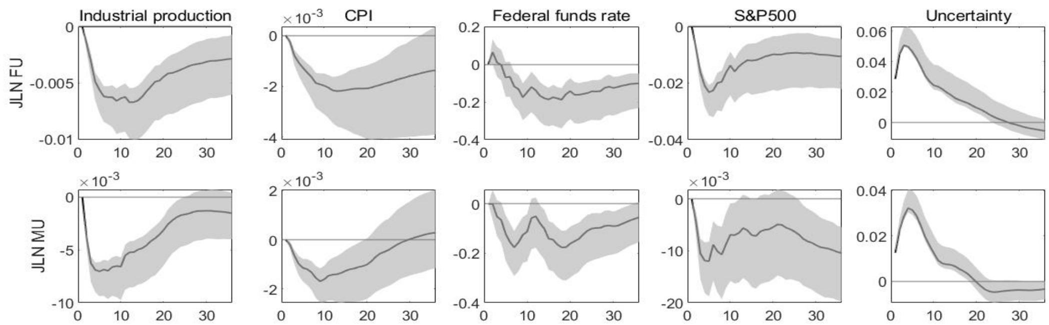
Note: This graph plots 36-month-horizon impulse response functions of relative income growth and relative wealth growth to the one standard deviation uncertainty shock in a larger-scale VAR model. The Cholesky ordering is the log of industrial production, the log of employment, the log of CPI, the log of real wage, weekly hours worked, the federal funds rate (with Wu-Xia shadow rate), the log S&P500, the log of real M2, the log of real housing prices, the log of real personal transfers, the uncertainty index, and each inequality metric. The shaded area is the bootstrap 90% confidence interval. Each row represents different uncertainty measures and each column represents a response of the income/wealth growth of different groups. The sample period is January 1976 to December 2019.

Figure A.8. Response of relative income (top) wealth (bottom) growth to uncertainty shocks: post-Great Moderation period



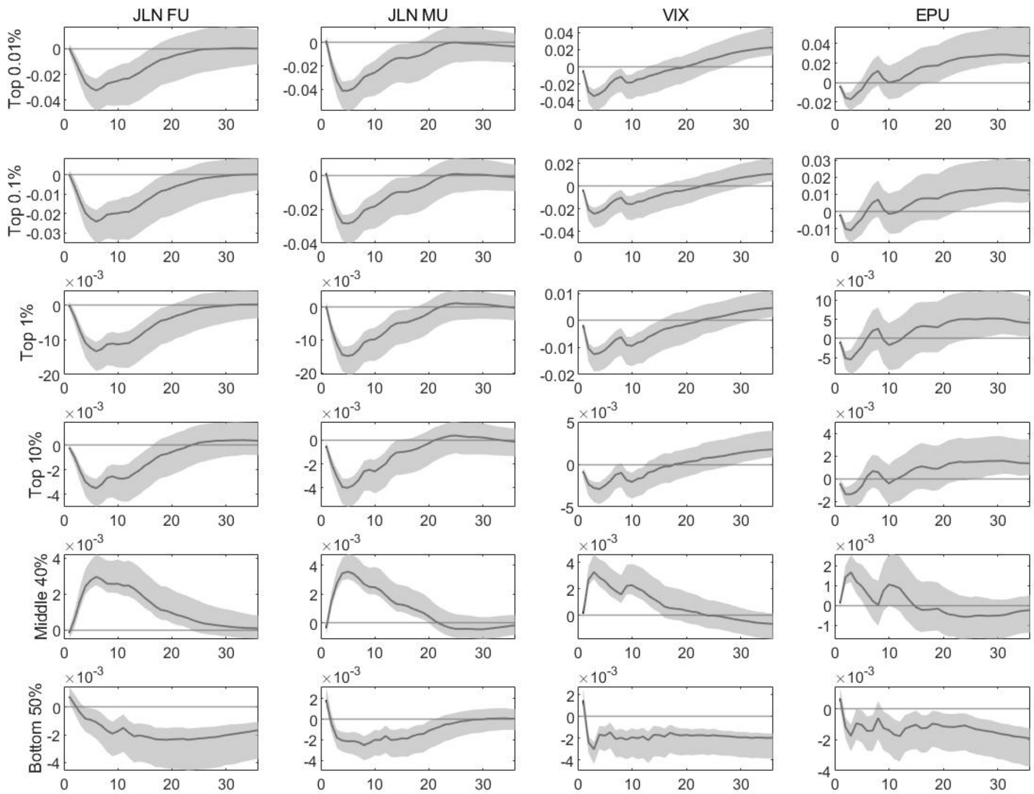
Note: This graph plots 36-month-horizon impulse response functions of relative income growth and relative wealth growth to the one standard deviation uncertainty shock. The shaded area is the bootstrap 90% confidence interval. Each row represents different uncertainty measures and each column represents a response of the income/wealth growth of different groups. The sample period is January 1984 to December 2019.

Figure A.9. The response of aggregate variables to uncertainty shocks including the COVID-19



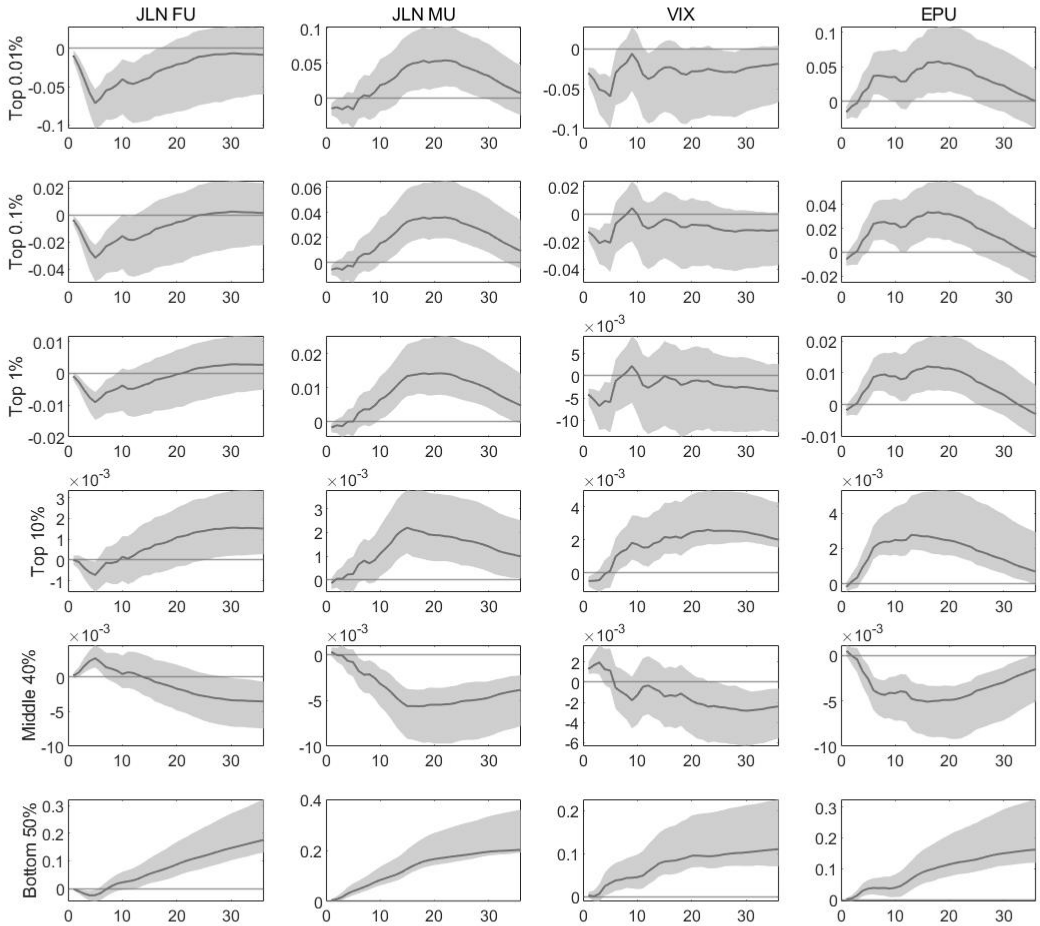
Note: This graph plots 36-month-horizon impulse response functions of macroeconomic variables to the one standard deviation uncertainty shock. The relative income growth of 10% is used as a measure of inequality, but its result is not presented in the figure. The shaded area is the bootstrap 90% confidence interval. Each row represents different uncertainty measures and each column represents the response of different macroeconomic variables. The sample period is January 1976 to December 2021.

Figure A.10. Response of relative income growth to uncertainty shocks including COVID-19



Note: This graph plots 36-month-horizon impulse response functions of relative income growth to the one standard deviation uncertainty shock. The shaded area is the bootstrap 90% confidence interval. Each row represents different uncertainty measures and each column represents a response of the income growth of different groups. The sample period is January 1976 to December 2021.

Figure A.11. Response of relative wealth growth to uncertainty shocks including COVID-19



Note: This graph plots 36-month-horizon impulse response functions of relative wealth growth to the one standard deviation uncertainty shock. The shaded area is the bootstrap 90% confidence interval. Each row represents different uncertainty measures and each column represents a response of the wealth growth of different groups. The sample period is January 1976 to December 2021.

Table A.1. The role of uncertainty shocks in explaining inequality including COVID-19

		JLN financial			JLN macro		
Income		H=12	H=24	H=36	H=12	H=24	H=36
	Top 0.01%	12.11%	9.15%	7.88%	19.40%	12.36%	10.47%
	Top 0.1%	15.61%	13.36%	12.10%	20.52%	14.05%	12.45%
	Top 1%	19.23%	18.04%	17.01%	22.11%	16.84%	15.72%
	Top 10%	15.24%	12.57%	11.73%	18.74%	13.14%	11.93%
	Middle 40%	26.23%	28.14%	26.86%	35.49%	30.45%	28.59%
	Bottom 50%	4.75%	11.53%	15.57%	11.52%	10.55%	9.33%
Wealth		H=12	H=24	H=36	H=12	H=24	H=36
	Top 0.01%	9.98%	15.38%	17.94%	8.31%	12.98%	12.81%
	Top 0.1%	10.67%	17.12%	19.58%	8.47%	13.81%	13.71%
	Top 1%	8.10%	14.73%	17.29%	7.07%	13.40%	13.87%
	Top 10%	0.36%	0.33%	0.98%	0.23%	0.31%	0.99%
	Middle 40%	3.51%	3.57%	3.57%	2.03%	4.22%	3.89%
	Bottom 50%	0.99%	2.03%	4.57%	1.94%	4.20%	3.40%

Note: The first row of the table shows the forecast error variance decomposition of relative income growths explained by uncertainty shocks over the three forecasting horizons. (H=12, 24, and 36 months). The second row of the table shows the forecast error variance decomposition of relative wealth growths explained by uncertainty shocks over the three forecasting horizons. (H=12, 24, and 36 months). The sample period is January 1976 to December 2021.