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Impact of Uncertainty Shocks on Income and Wealth Inequality

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Sangyup Choi
Yonsei University
Centre for Applied Macroeconomic Analysis, ANU

Jeeyeon Phi
Yonsei University

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JEL Classification

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Address for correspondence:

(E) cama.admin@anu.edu.au

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Impact of Uncertainty Shocks on Income and Wealth Inequality[*]

Sangyup Choi[†]
Yonsei University and CAMA
(Australia National University)

Jeeyeon Phi[‡]
Yonsei University

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[†] School of Economics, Yonsei University, 50 Yonsei-ro, Seodaemun-gu, Seoul 03722, South Korea.
Center for Applied Macroeconomic Analysis (CAMA), Crawford School of Public Policy, Australian National University.
Email address: sangyupchoi@yonsei.ac.kr

[‡] School of Economics, Yonsei University, 50 Yonsei-ro, Seodaemun-gu, Seoul 03722, South Korea.
Email address: jeeyeonphi@yonsei.ac.kr.

I. INTRODUCTION

The global financial crisis and the recent COVID-19 pandemic were characterized by an unprecedented level of uncertainty about the future course of the economy. At the same time, policymakers and economists worldwide are concerned about the distributional consequences of these events because not everyone is equally affected. Relatedly, many theoretical studies model uncertainty as a dispersion of exogenous shocks that affect 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 further motivate policymakers to address the negative effects of uncertainty shocks.

Surprisingly, despite significant advancements in measuring and understanding uncertainty's macroeconomic effects, there is limited empirical evidence linking uncertainty to inequality. Even recent survey papers on the determinants of inequality have not explored the role of uncertainty in driving inequality (Colciago et al., 2019; Furceri and Ostery, 2019). Prior studies on the cyclical drivers of inequality have predominantly focused on various policy changes, especially changes in monetary policy (Coibion et al., 2017; Mumtaz and Theophilopoulou, 2017; Furceri et al., 2018; Auclert, 2019; Amberg et al., 2022; Samarina and Nguyen, forthcoming) and, to a lesser extent, fiscal policy (García-Peñalosa and Turnovsky, 2007; Anderson et al., 2016).

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). To the best of our knowledge, there have been only three published papers (De Giorgi and Gambetti, 2017; Fischer et al., 2021; Theophilopoulou, 2022) investigating the effect of uncertainty shocks on income inequality as of the writing of this paper and none on wealth inequality.[2] To

[1] For example, theoretical studies like Kasa and Lei (2018) and Jovanovic and Ma (2022) propose a mechanism where heightened uncertainty results in higher top wealth shares and a more dispersed distribution of outcome growth, thereby contributing to increased inequality.

[2] De Giorgi and Gambetti (2017) examined the effect of three types of uncertainty shocks on consumption inequality in the United States using CEX data from 1984Q1 to 2010Q4. They discovered that consumption inequality decreases after the uncertainty shock, mainly due to a larger consumption reduction in the 10th decile. Fischer et al. (2021) investigated the response of income inequality at the state level in the United States to nationwide uncertainty shocks from 1985Q1 to 2017Q1. Using the Gini coefficient as a measure of income inequality, they found that uncertainty shocks generally reduce income inequality in most regions. Theophilopoulou (2022) estimated the impact of uncertainty shocks on disposable income, wage, and consumption inequality in the United Kingdom from 1970Q1 to 2018Q1. Her findings indicated that wage and disposable income inequality decrease following the uncertainty shock.

address this gap, we aim to conduct a systematic empirical analysis of how uncertainty shocks have influenced both income and wealth inequality in the United States over the past four decades.

In contrast to the aforementioned studies, our research has distinct characteristics. First, while previous studies did not examine wealth inequality due to measurement challenges, we investigate both income and wealth inequality using a novel database that includes data on the super-rich (e.g., top 0.1% or 0.01%), information that was typically unavailable in earlier survey-based studies. Second, unlike previous research using quarterly to annual data, our analysis provides monthly data consistently spanning over 45 years, resulting in a significantly larger number of observations.[3] Third, we differentiate between changes in labor income inequality and non-labor income inequality to gain deeper insights into the pathways through which uncertainty impacts inequality, an aspect not explored in prior studies.

Fourth, we provide a comprehensive analysis by comparing the responses of market income inequality and disposable income inequality to uncertainty shocks. Previous studies often focused on either market income or disposable income, potentially contributing to the lack of consensus in their findings. Fifth, we explore the impact of different sources of uncertainty by comparing the effects of financial uncertainty with those of macroeconomic uncertainty. Lastly, we assess the effect of uncertainty shocks on income and wealth inequality both with and without the recent COVID-19 pandemic. This allows us to determine if this unprecedented event has altered the relationship between uncertainty and inequality. By incorporating these novel aspects into our research, we aim to provide a more comprehensive and nuanced understanding of the link between uncertainty and income and wealth inequality.

To this end, 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. Our VAR model incorporates the standard macroeconomic and financial variables that characterize the U.S. economy, along with various measures of income and wealth inequality sourced from Blanchet et al. (2022). Recently, Blanchet et al. (2022) constructed distributional data on income and wealth at a monthly frequency, expanding on their earlier work that relied on annual data from Saez and Zucman (2016) and Piketty et al. (2018).

Our findings reveal that uncertainty shocks have heterogeneous effects on different income and wealth groups, leading to variations in inequality levels. The implications of uncertainty shocks

[3] Using monthly-frequency data alleviates the concern about timing issues when using Cholesky ordering and allows us to observe interesting short-run dynamics of inequality following uncertainty shocks. By leveraging monthly-frequency data, we enhance the accuracy and granularity of our analysis.

on inequality are economically significant, with the response to a one standard deviation uncertainty shock being comparable to a positive monetary policy shock of 50 basis points in the same VAR model. Nevertheless, it is important to acknowledge that different inequality measures may not always yield consistent conclusions, a limitation highlighted by Heathcote et al. (2010). This caveat underscores the complexity of understanding the relationship between uncertainty shocks and inequality, prompting the need for assessing the entire distribution when evaluating the effects of such shocks.

For example, while the overall inequality—representing the income gap between the rich (top 10%) and the poor (bottom 50%)—somewhat widens after the uncertainty shock, it masks significant variations within the distribution. Specifically, the upper inequality, which measures the income gap between the rich and the middle (middle 40%), narrows significantly in response to uncertainty shocks. On the other hand, the lower inequality, reflecting the gap between the middle and the poor, widens substantially. We offer insights into the underlying reasons for these contrasting effects. The decline in business and interest income accounts for the narrowing of the upper inequality, while the increase in real wages for the employed, despite rising unemployment, explains the widening of the lower inequality. Decomposing market income into labor and non-labor income provides further evidence supporting these explanations. By considering the distributional consequences comprehensively, we gain a more nuanced understanding of how uncertainty influences inequality across different income groups.

Interestingly, the distributional consequence of uncertainty shocks changes once we incorporate the role of redistribution policy by examining the response of disposable income inequality instead. This difference in income definitions provides a rationale for the lack of consensus among existing studies on the uncertainty-inequality relationship. In this case, uncertainty shocks tend to lower inequality across the income distribution, alleviating the concern that rising uncertainty widens inequality. Indeed, we find that transfers increase in response to uncertainty shocks. A tighter correlation between consumption and disposable income than market income can explain why the existing studies found a decline in consumption inequality after uncertainty shocks (e.g., De Giorgi and Gambetti, 2017).

Given the significant proportion of U.S. households with near-zero or even negative wealth holdings, our focus in this study is on the concentration of wealth among rich households (top 10% or above) to understand how wealth inequality responds to uncertainty shocks. Our analysis reveals that uncertainty shocks tend to reduce wealth inequality, although the estimated effects are less precise compared to income inequality. Notably, the decline in wealth concentration becomes more pronounced when we examine even richer households (e.g., top 1%, 0.1%, and 0.01%). This pattern can be rationalized by the fact that richer households have a disproportionately higher share of financial assets, whose values experience substantial declines in response to uncertainty shocks. On the other hand, a relatively smaller decline in housing prices, which constitute a significant portion of middle-class households' wealth, explains why their wealth is less adversely affected compared to rich households.

To gain a deeper understanding of how uncertainty impacts inequality, we carefully investigate how the estimated effects vary depending on the source of uncertainty. Our analysis compares the effects of uncertainty shocks originating from financial markets with those arising from the macroeconomy. We find that both types of uncertainty shocks have similar qualitative effects on income and wealth inequality. However, the main transmission channels appear somewhat different. Uncertainty shocks in financial markets have a more substantial impact on financial variables, such as stock prices or interest rates, while uncertainty shocks from the macroeconomy have a more pronounced effect on macro aggregates like output or unemployment. When we take into account the influence of the COVID-19 pandemic, we observe a divergent path between financial uncertainty and macroeconomic uncertainty.

The remainder of this paper is organized as follows. Section II explains the main data, including new high-frequency measures of income and wealth inequality, 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.

Measures of inequality. Our inequality measures rely on monthly income and wealth distribution data, recently compiled by Blanchet et al. (2022). These data are publicly accessible at https://realtimeinequality.org/ and are regularly updated once the primary national income statistics are available.[4] The dataset allows tracking of the monthly national income and wealth distribution. It provides income distribution data not only for market income but also for labor

[4] 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).

income, non-labor income, and disposable income, enabling a comprehensive analysis. The values are adjusted for inflation, using 2021 as the base year, yielding real income and wealth figures. The data cover the period from January 1976 to December 2021 and are divided into six groups based on income or wealth ranking: top 0.01%, top 0.1%, top 1%, top 10%, middle 40%, and bottom 50%. For more detailed information on the dataset's construction, refer to Section A in the online appendix.

While the database lacks a well-known single-statistic inequality measure like the Gini index, we offer various inequality measures to present a comprehensive view of inequality changes.[5] Our baseline income inequality measure is defined by the ratio of the average income of the top 10% to that of the bottom 50% ($\frac{\bar{P}_{90,100}}{\bar{P}_{0,50}}$). Furthermore, following the approach of Theophilopoulou (2022), we decompose the overall inequality measure into "upper inequality" ($\frac{\bar{P}_{90,100}}{\bar{P}_{50,90}}$) and "lower inequality" ($\frac{\bar{P}_{50,90}}{\bar{P}_{0,50}}$) using the following relationship:

$$\frac{\bar{P}_{90,100}}{\bar{P}_{0,50}} = \frac{\bar{P}_{90,100}}{\bar{P}_{50,90}} \times \frac{\bar{P}_{50,90}}{\bar{P}_{0,50}}, \tag{1}$$

which allows us to identify which part of the distribution primarily drives changes in overall inequality following uncertainty shocks.[6]

However, it is not possible to construct the same percentile ratio measures for wealth distribution due to a substantial proportion of U.S. households having negative net wealth. Furthermore, wealth concentration is considerably stronger than income concentration, as evidenced in Figures A.1 and A.2 in the online appendix. As a result, most existing studies have primarily focused on examining the top end of the wealth distribution rather than the middle or bottom (e.g., Saez and Zucman, 2016; Vermeulen, 2016). Therefore, to assess wealth inequality, we use the share of wealth held by the top 10% as a baseline measure and additionally consider the top 1%, 0.1%, and 0.01% wealth shares to gain a comprehensive understanding of wealth distribution and its

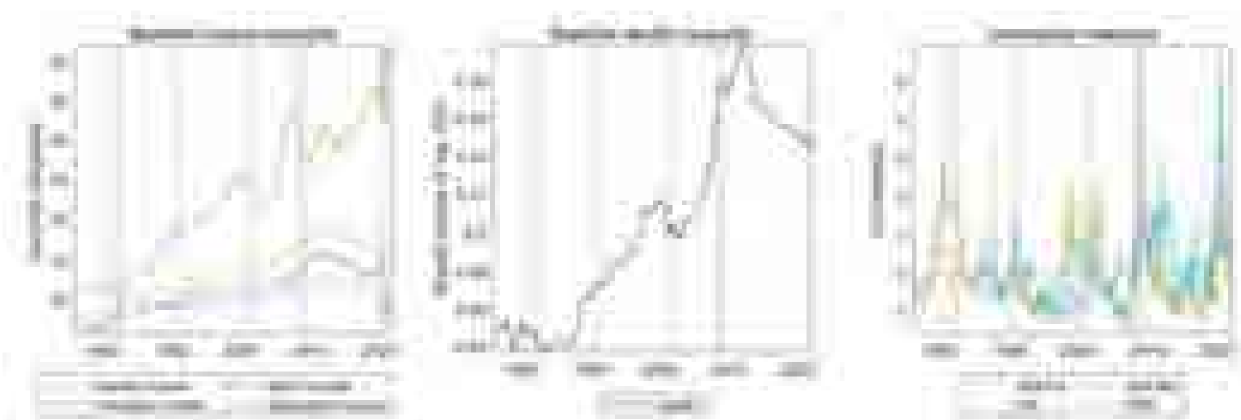
[5] Indeed, while the Gini index is a widely used measure of inequality, it lacks information about the specific location of households along the distribution that are most impacted by inequality (Mumtaz and Theophilopoulou, 2017). To address this limitation, we favor our percentile ratio measure, which provides a more detailed perspective on the distributional effects of inequality. Additionally, we construct sub-indices using Equation (1), allowing us to examine changes in specific segments of the distribution and better understand how different parts of the population are affected by uncertainty shocks.

[6] Upper inequality is defined as the ratio of average income of the top 10% to that of the middle 40% ($\frac{\bar{P}_{90,100}}{\bar{P}_{50,90}}$), whereas lower inequality is defined as the ratio of average income of the middle 40% to that of the bottom 40% ($\frac{\bar{P}_{50,90}}{\bar{P}_{0,50}}$).

response to uncertainty shocks. This approach allows us to focus on the concentration of wealth among the wealthiest segments of the population, which was not feasible in prior studies, thereby providing valuable insights into the impact of uncertainty on wealth inequality.

The left panel of Figure 1 depicts the evolution of baseline inequality measures across various income categories, while the middle panel illustrates the changes in baseline wealth inequality over time. Notably, there is a long-term trend of rising inequality in each income category, aligning with previous observations indicating an acceleration of U.S. inequality since the 1980s (Piketty et al., 2018). However, it is essential to recognize significant heterogeneity across income categories, underscoring the significance of decomposing income inequality to better understand its dynamics and distributional implications.

Figure 1. Evolution of income inequality, wealth inequality, and uncertainty



Note: This graph plots the evolution of baseline inequality measures (the top 10% to the bottom 50% average income ratio) for each income category (left), baseline wealth inequality measure (wealth share of the top 10%, middle), and four uncertainty measures (right). All uncertainty measures in the figure are standardized to have zero mean and unit variance. The sample period for all variables except for the VIX and the EPU index is January 1976 to December 2021; for the VIX, January 1990 to December 2021; and for the EPU index, January 1985 to December 2021. Shaded areas denote NBER recession dates.

First, non-labor income inequality has increased at a much faster pace than labor income inequality over time. However, non-labor income inequality tends to decline sharply during recessions, likely due to declines in business income and interest/dividend income. Second, disposable income inequality demonstrates the least increase over time, primarily attributed to the impact of redistribution policies that aim to address income disparities. Third, due to the significant share of labor income in the overall income composition for a wide segment of the population, market income inequality closely mirrors labor income inequality. Fourth, these measures display notable fluctuations over business cycles, underscoring the importance of considering cyclical changes in inequality. Given the erratic pattern of inequality measures during the pandemic period (largely driven by unprecedented increases in unemployment and substantial fiscal stimulus), we exclude this period from our baseline exercise.

The baseline wealth inequality measure portrays a similar trend, although there has been some alleviation in wealth concentration over the last decade. The share of wealth held by the top 10% was approximately 65% in the early 1980s but rose to 80% in the early 2010s. For a comprehensive understanding of the evolution of inequality, including all income and wealth groups (including those above the top 1%), refer to Figures A.1 and A.2 in the online appendix. These figures provide detailed changes in the share of income and wealth across various groups over time, further demonstrating the dynamics of inequality in both income and wealth distribution.

Measures of uncertainty. Uncertainty is an inherently unobservable concept, necessitating the use of empirical proxies to investigate the impact of uncertainty shocks on income and wealth inequality. To better understand how the source of uncertainty influences its effect on inequality, we employ various empirical measures of uncertainty that capture different aspects of the economy.[7] In our baseline analysis, we utilize two widely-used measures of uncertainty found in the literature: JLN financial and macroeconomic uncertainty indices, as proposed by Jurado et al. (2015). These indices are constructed using the same econometric model but are designed to capture different sources of uncertainty, namely financial versus macroeconomic origin. The financial (macroeconomic) uncertainty index is calculated as the weighted sum of individual uncertainty measures associated with the underlying financial (macroeconomic) variables. Individual uncertainty is constructed by considering the conditional volatility of the unforecastable component of the series in the future, effectively removing the forecastable component.[8] For further details on the construction of these uncertainty indices, refer to Section A in the online appendix, where we provide a comprehensive explanation of the methodology employed.

We select the JLN financial and macroeconomic uncertainty indices as our baseline measures due to their direct comparability and availability for the entire sample period of the study. Kozeniauskas et al. (2018) have also demonstrated that these indices exhibit the highest overall correlation with other uncertainty measures, confirming their representativeness. In our analysis, we

[7] 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), (iii) applying a text-mining technique to search for uncertainty-related words in newspapers or other documents (Baker et al., 2016), and (iv) measuring forecast dispersion or disagreement among survey respondents (Lahiri and Sheng, 2010).

[8] 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.

focus on one-month ahead (h=1) uncertainty as our baseline measure, but we have verified that the key results remain consistent when using one-year ahead (h=12) uncertainty. As a robustness check, we incorporate other widely-used measures of uncertainty, namely the VIX and Economic Policy Uncertainty (EPU) index constructed by Baker et al. (2016).[9] While these alternative measures are available for shorter periods (from 1990 for VIX and 1985 for EPU), they enhance the reliability and validity of our results, ensuring that our conclusions are not dependent on the specific choice of uncertainty indices.

The right panel in Figure 1 displays the evolution of the four standardized uncertainty measures, facilitating easy comparison. Notably, these measures tend to spike during periods of heightened uncertainty, such as the global financial crisis or the COVID-19 outbreak. While they share a commonality, their correlation is not perfect, as indicated in Table A.1 in the online appendix. This suggests that they capture distinct aspects of uncertainty related to the U.S. economy.[10]

Other macroeconomic and financial variables. Our VAR model incorporates a standard set of macroeconomic and financial variables, following existing research on the impact of uncertainty shocks on the U.S. economy (Bloom, 2009; Leduc and Liu, 2016; Basu and Bundick, 2017). The baseline model includes the following monthly-frequency variables: industrial production, the unemployment rate, the consumer price index (CPI), the stock market index (S&P500), and the federal funds rate. Additionally, during the zero lower bound (ZLB) period, we use the Wu–Xia shadow rate (Wu and Xia, 2016). These variables also provide insights into the mechanisms through which heightened uncertainty impacts income and wealth inequality.

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[9] According to Bloom (2009), in general, the VIX index tends to temporarily jump about twice on average after major shocks. The VIX primarily captures uncertainty in financial markets and is widely used due to its real-time availability. On the other hand, the EPU index, as described by Baker et al. (2016), encompasses uncertainty related to "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) constructed this index using a narrative approach, incorporating news coverage of policy-related economic uncertainty from ten major newspapers in the United States.

[10] To facilitate the interpretation of our findings, we categorized the four uncertainty measures into two groups based on their sources: financial and macroeconomic. This grouping decision is motivated by recent research indicating that the transmission of uncertainty shocks can differ depending on whether they originate from financial or macroeconomic sources (Carriero et al., 2018; Ludvigson et al., 2021; Choi and Yoon, 2022). The JLN financial uncertainty index and the VIX display a high correlation of 0.82, supporting their classification as financial uncertainty measures. Similarly, the EPU index demonstrates the highest correlation (0.56) with the JLN macroeconomic uncertainty index, validating the grouping of these measures as capturing macroeconomic uncertainty.

B. Vector Autoregression model

In this subsection, we outline the empirical framework used in this analysis. We employ a standard VAR model to estimate the impact of uncertainty shocks on income and wealth inequality while incorporating the dynamic relationship with other aggregate variables. The baseline VAR model consists of (i) standard macroeconomic and financial variables that characterize the U.S. economy and are common to each VAR model, (ii) an uncertainty measure, and (iii) various inequality measures, which are introduced sequentially into the VAR system. Our variable selection aligns with seminal studies investigating the aggregate effects of uncertainty shocks, such as Bloom (2009), Jurado et al. (2015), and Baker et al. (2016), with the addition of inequality measures.

For a consistent and straightforward comparison between exercises, we employ the same model when assessing the distributional impacts of financial uncertainty shocks and macroeconomic uncertainty shocks.[11] Any divergences in their transmission channels would be reflected in distinct estimated impulse response functions (IRFs) for the underlying variables. The following general representation summarizes the structural VARs employed in this study:

$$Ay_t = c + \sum_{k=1}^{p} F_k y_{t-k} + u_t, \tag{2}$$

where y_t is an $n \times 1$ vector of the aforementioned variables ($n = 7$ 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. 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 (2):

$$y_t = A^{-1}c + \sum_{k=1}^{p} B_k y_{t-k} + A^{-1}\Sigma\epsilon_t, \qquad \epsilon_t \sim N(0, I_n), \tag{3}$$

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

[11] In existing studies concerning uncertainty shocks within the VAR literature, a consistent practice has been to utilize a uniform model when altering the uncertainty measure (e.g., Bloom, 2009; Caldara et al., 2016; Leduc and Liu, 2016; Carriero et al., 2018; Choi and Yoon, 2022; Theophilopoulou, 2022).

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

where σ_i denotes the standard deviation of each structural shock. In our seven-variable VAR model, recursive identification is achieved through the Cholesky ordering as follows: industrial production, unemployment rate, CPI, federal funds rate (including the Wu-Xia shadow rate), inequality measure, uncertainty index, and S&P500. This ordering closely aligns with the approach of Jurado et al. (2015) and indicates that uncertainty shocks do not have an immediate impact on the inequality measure and other macroeconomic variables, except for a forward-looking stock market variable. Conversely, shocks to macroeconomic variables can contemporaneously influence uncertainty and inequality. To validate the robustness of our results, we also explore alternative orderings that allow for a simultaneous effect of uncertainty shocks on macroeconomic variables and inequality.

To ensure stationarity in the VAR system, we take the (log) difference of non-stationary variables. The results of the augmented Dickey-Fuller tests are available in Table A.2 of the online appendix. For the analysis, we employ a lag of three (p=3), which is a conservative choice compared to the suggestions of the Akaike and Bayesian information criteria (ranging between one and two lags). However, altering the number of lags has minimal impact on qualitative findings.

III. Empirical Findings

A. Uncertainty shocks and income inequality

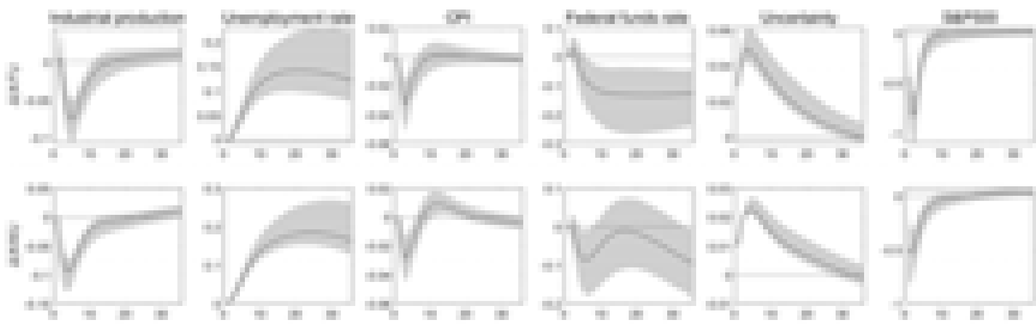
Response of aggregate variables. Initially, we verify the consistency of the main findings in the literature within our primary specification and sample period. This entails analyzing the responses of aggregate variables to both types of uncertainty shocks. When presenting aggregate dynamics of uncertainty shocks, we employ the aforementioned overall income inequality measure, while other inequality measure responses will be provided subsequently.[12]

Figure 2 confirms the well-known adverse effect of uncertainty shocks on the real economy, holding true for both uncertainty measures. Similar to findings by Leduc and Liu (2016) and Basu and Bundick (2017), we observe a significant decline in CPI following uncertainty shocks, indicating that such shocks act as negative aggregate demand shocks. Consequently, the Federal Reserve responds by actively reducing the short-term policy rate. Notably, the impact on stock returns is

[12] Through sequential replacement of the overall inequality measure with alternative measures, we verify that the response of aggregate variables to the uncertainty shock remains consistent, independent of the chosen income inequality measure.

more pronounced for financial uncertainty shocks, while unemployment is more affected by macroeconomic uncertainty shocks. This finding is consistent with Carriero et al. (2018) and indicates a successful identification of each type of uncertainty shock. Nonetheless, their qualitative effects remain similar, which supports our decision to employ the same model for parsimony.

Figure 2. Response of aggregate variables to uncertainty shocks



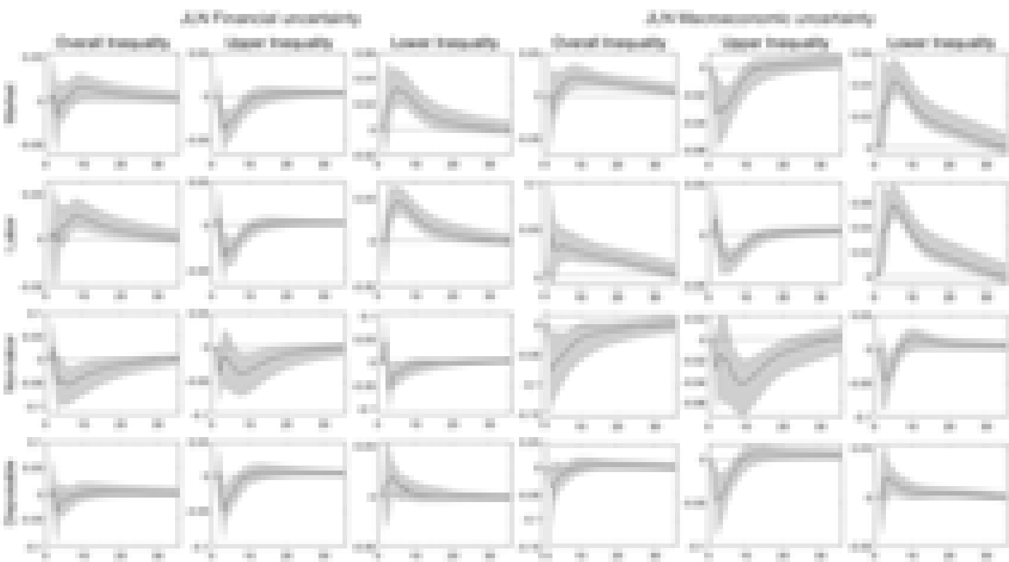
Note: This graph plots the 36-month-horizon IRFs of the aggregate variables to one standard deviation uncertainty shock. The shaded area represents the bootstrap 90% confidence interval. Each row represents different uncertainty measures and each column represents the responses of different macroeconomic variables. The sample period is January 1976 to December 2019.

Response of market income inequality. Figure 3 presents the key findings of this paper, focusing on the distributional consequences of uncertainty shocks. Each row displays inequality measures based on various income definitions, while each column illustrates upper and lower inequality, along with overall inequality (as defined in Section II.A). The responses are presented separately for financial uncertainty and macroeconomic uncertainty.

The top panel of Figure 3 presents the response of market income inequality, the primary focus of our analysis. Following both types of uncertainty shocks, overall market income inequality shows a slight increase, although the response is statistically insignificant for financial uncertainty shocks. However, this observation overlooks significant heterogeneity when different parts of the income distribution are considered. Equation (1) demonstrates that changes in overall inequality can be approximated by the sum of changes in upper and lower inequality after a log transformation. Therefore, we proceed to present the responses of upper and lower inequality measures in the subsequent columns.

Notably, uncertainty shocks lead to a substantial increase in lower inequality, while upper inequality experiences a significant decrease. This implies a narrowing of inequality between the rich and middle classes and a widening between the middle and poor after uncertainty shocks. As a result, the overall inequality shows only a minor change despite the pronounced impact of uncertainty shocks on the income distribution. This emphasizes the importance of considering the entire distribution to avoid misleading conclusions regarding the distributional consequences of uncertainty shocks.[13] Additionally, in Figure C.1 of the online appendix, we demonstrate the response of income inequality at the very top (the ratio of the average income of the top 1% and beyond to that of the top 10%) to uncertainty shocks. These inequality measures decline, indicating that the so-called super-rich are more adversely affected by uncertainty shocks.

Figure 3. Response of income inequality to uncertainty shocks



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

How large are the distributional effects of uncertainty shocks? To gauge their economic magnitude, we utilize the same VAR model to estimate the distributional effect of monetary policy shocks. An exogenous monetary tightening results in an immediate decline in upper inequality, possibly due to reduced business income, and a somewhat sustained increase in lower inequality due to its adverse impact on the labor market, resulting from an economic slowdown. A back-of-the-envelope calculation suggests that the distributional effects of one standard deviation uncertainty

[13] Our finding complements the work of Fischer et al. (2021), who demonstrated that nationwide uncertainty shocks decrease the income Gini coefficients of most U.S. regions by highlighting that this conclusion depends on whether we examine the upper or lower income distribution. They further suggested that distributional consequences may vary across different inequality measures, as they found a negative association between the share of the top 1% and changes in income inequality, while the top 10% share showed a positive association with changes in income inequality after uncertainty shocks at the state level.

shocks are comparable to approximately 50 basis points of exogenous monetary policy tightening, signifying their economic significance.[14]

Inequality in labor income vs. non-labor income. Decomposing the effects of uncertainty shocks into labor income and non-labor income components offers insights into the source of changes in market income inequality, particularly when there is substantial heterogeneity in the income composition across the distribution (e.g., Jones, 2015; Berisha et al., 2018; Oh and Rogantini Picco, 2020). The second and third panels in Figure 3 present the results by replacing market income inequality with labor and non-labor income inequality, respectively, revealing significant heterogeneity between the two income sources. On the one hand, the response of labor income inequality mirrors that of market income inequality, with the poorer group being more adversely affected than the middle group by uncertainty shocks due to the impact of slowed economic activity and rising unemployment through the earnings heterogeneity channel.[15]

On the other hand, non-labor income inequality uniformly decreases across the distribution in response to both financial and macroeconomic uncertainty shocks. This uniform decrease can be attributed to the income composition channel. Given the sensitivity of business income to uncertainty shocks and the decline of interest income with monetary policy responses, non-labor income significantly reduces for rich households. In contrast, as poor households have relatively limited business and interest income to begin with, they experience less adverse effects from uncertainty shocks, thereby contributing to a decrease in lower inequality.

Role of redistribution policy. To shed light on the ultimate effect of uncertainty shocks on inequality that is more relevant for household welfare, we conduct a similar analysis using disposable income instead of market income. As high-frequency consumption inequality data is not available, we leverage the strong correlation between disposable income inequality and consumption inequality (e.g., Aguiar and Bills, 2015) to understand how uncertainty shapes consumption inequality.[16]

The last row in Figure 3 reveals that while the implication for upper inequality remains similar, the increase in lower inequality is significantly mitigated and becomes statistically

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[14] The online appendix C offers comprehensive details on this analysis, and Figure C.2 presents a summary of the response of aggregate variables and market inequality measures to a 50 basis point positive monetary policy shock.

[15] High-income households depend more on business and capital income and these income sources decline after the uncertainty shock. In contrast, the employment status of low-income households is most vulnerable to economic contractions induced by the uncertainty shock.

[16] Consumption inequality is often measured by using quarterly Consumer Expenditure Surveys.

insignificant. This observation aligns with the income composition channel, indicating that low-income households rely more on transfers, leading to income redistribution to the poor in response to uncertainty shocks. Consequently, uncertainty shocks tend to reduce overall disposable income inequality, in contrast to market income inequality. Our findings are consistent with Theophilopoulou (2022), who reported a decline in disposable income inequality after uncertainty shocks in the U.K. economy using similar empirical methods and uncertainty measures. Moreover, our findings provide a rationale for De Giorgi and Gambetti (2017)'s main conclusion that uncertainty shocks decrease U.S. consumption inequality and Meyer and Sullivan (2013)'s finding consumption inequality declined while income inequality rose during the Great Recession.

B. Robustness checks and additional exercises

This section presents a comprehensive range of robustness checks and additional exercises, including forecast error variance decomposition and historical decomposition. For brevity, we display the robustness checks for market income inequality in Figure 4, while Figures B.1 to B.8 in the online appendix B provide the complete results for all exercises, encompassing labor income, non-labor income, and disposable income inequality. Overall, the main finding that uncertainty shocks lead to heterogeneous distributional effects, reducing upper market income inequality while widening lower market income inequality, remains consistent across alternative specifications.

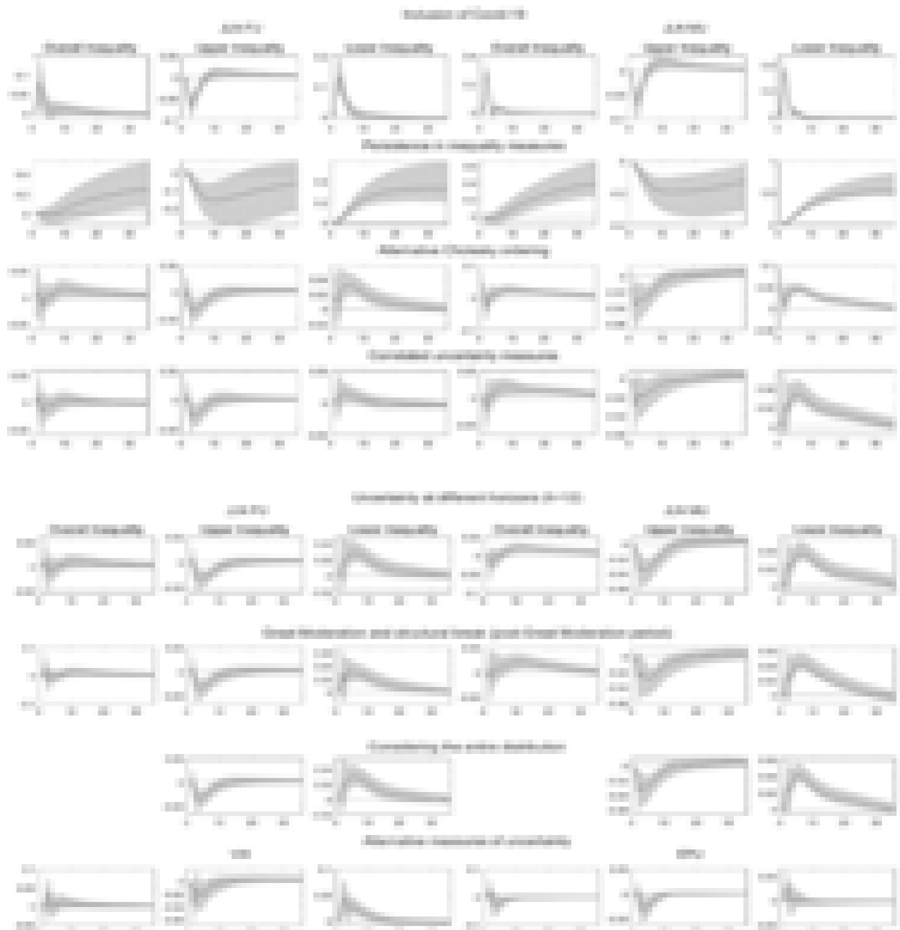
Inclusion of Covid-19. As shown in Figure 1, the COVID-19 pandemic has induced an unprecedented level of distributional consequences. Labor income inequality surged due to a sudden rise in unemployment, while disposable income inequality notably decreased, possibly attributable to substantial fiscal stimulus measures (e.g., Chetty et al., forthcoming). While this period was excluded from the baseline analysis due to the erratic behavior of macroeconomic variables and inequality metrics, it could have significantly altered the relationship under study.[17]

To explore this possibility, we re-estimate our baseline model with additional observations since 2020. As depicted in the first row of Figure 4 (and associated Figure B.1 in the online appendix), the inclusion of the COVID-19 event strengthens our findings. The responses of each inequality measure are more precisely estimated, with a notable increase in the quantitative effects of uncertainty shocks on lower inequality, leading to a substantial overall inequality rise. This is

[17] Following Lenza and Primiceri (2022), we excluded COVID-19 observations from the baseline analysis, as our aim is to estimate the general relationship between uncertainty and inequality, rather than forecasting the future evolution of the economy.

consistent with a larger adverse effect on the labor market compared to the baseline sample.[18] Moreover, Figure B.1 in the online appendix reveals a significant decrease in disposable income inequality across the distribution, likely attributable to a targeted fiscal response to the pandemic shock (Han et al., 2020).

Figure 4. Uncertainty shocks and income inequality: robustness checks



Note: This graph plots the 36-month-horizon IRFs of market income inequality measures to one standard deviation uncertainty shock. The shaded area represents the bootstrap 90% confidence interval. Each row corresponds to different robustness checks outlined in Section III.B. To save space, we delegate the rest of the results to Figures B.1. to B.8 in the online appendix.

Persistence in inequality measures. To address the non-stationarity in baseline inequality measures used in VARs, we differenced them to ensure stationarity. However, it is important to note that the (near) unit root property of inequality measures could imply persistent effects of any transitory

[18] Refer to Figure C.3 in the online appendix for the responses of aggregate variables to uncertainty shocks using the extended sample.

shock, as discussed in Christopoulos and McAdam (2017). Additionally, some related studies (e.g., Mumtaz and Theophilopoulou, 2017; Furceri et al., 2018; Fischer et al., 2021; Theophilopoulou, 2022; Samarina and Nguyen, forthcoming) have included their inequality measures in level. While we lack a strong theoretical stance on whether uncertainty shocks should have a persistent effect on inequality, we test the robustness of our findings by including inequality measures in levels, which also enables comparison with existing studies. As shown in the second row of Figure 4, the qualitative implications of the uncertainty-inequality relationship remain unchanged, although the responses become more persistent, as expected.

Alternative Cholesky ordering. We test the robustness of our findings using an alternative variable ordering, following Bloom (2009), where the uncertainty variable is placed second in the VAR system, after the stock market variable. This recursive ordering assumes that uncertainty is exogenous to the macroeconomy and inequality. To account for the contrasting evidence on the exogeneity of uncertainty (Fajgelbaum et al., 2017; Ludvigson et al., 2021), we explore both types of identifying assumptions to ensure balanced conclusions.[19] As shown in the third row of Figure 4, the ordering of the uncertainty variable has little impact on its distributional consequences. This outcome is expected since our primary focus is on the response of disaggregated variables (i.e., inequality measures), which are less likely to be affected by reverse causality concerns. In other words, while rising uncertainty may be an endogenous response to macroeconomic developments, it is less plausible that changes in the income or wealth of specific groups drive uncertainty about the U.S. economy.

Correlated uncertainty measures. We analyze each measure of uncertainty separately to explore potential differences in the distributional consequences of uncertainty shocks based on their sources. However, due to the positive correlation between financial and macroeconomic uncertainty measures (0.58), this exercise may not provide a conclusive answer to our question. To address this, we include both types of uncertainty measures in the VAR system. Yet, economic theory does not offer a clear answer regarding the relative exogeneity between the two sources of uncertainty. To err on the side of caution, we place the financial uncertainty index after the macroeconomic uncertainty index when estimating the effect of financial uncertainty shocks, and vice versa. While the statistical significance of the IRFs becomes slightly weaker, the qualitative results remain consistent, suggesting some orthogonality between financial and macroeconomic uncertainty (see the fourth row in Figure 4).

[19] 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.

Uncertainty at different horizons. In the baseline analysis, we focused on short-run measures of uncertainty using a one-month-ahead forecasting horizon for financial or macroeconomic time series (i.e., h=1 for $U_t^F(h)$ or $U_t^M(h)$). However, considering the potential differences between one-year-ahead and one-month-ahead uncertainty effects, we re-estimated the baseline model with a longer forecasting horizon (i.e., h=12).[20] As shown in the fifth row of Figure 4, our main finding remains robust.

Great Moderation and structural break. Given the structural break in the U.S. economy during the 1980s, with changes in the behavior of macroeconomic variables after the Volcker period (i.e., the Great Moderation), assuming parameter stability in our sample spanning both pre and post-Volcker periods may not be ideal.[21] To address this concern, we re-estimated the VAR model using observations from 1984M1 only. As shown in the sixth row of Figure 4, our main findings regarding the distributional consequences of uncertainty shocks remain consistent.

Considering the entire distribution. In our baseline analysis, we included three types of inequality measures (overall, upper, and lower) separately to ensure model parsimony. However, recognizing the significance of evaluating the entire distribution, we now include both upper and lower inequality measures together in the VAR system.[22] We cannot include the overall inequality measure due to perfect collinearity after taking logs as per Equation (1). The results in the seventh row of Figure 4 demonstrate that considering the entire distribution does not alter our main findings.

Alternative measures of uncertainty. In the final robustness exercise, we examine the responses using alternative measures of uncertainty (the VIX instead of JLN financial uncertainty and the EPU index instead of JLN macroeconomic uncertainty). The results in the last row of Figure 4 reaffirm the consistency of our qualitative findings for market income inequality with these alternative measures.[23]

Contribution of uncertainty shocks to income inequality. Table 1 provides the contribution of the uncertainty shocks to the forecast error variance decomposition (FEVD) of each income inequality

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[20] For example, one-year-ahead uncertainty may capture more pervasive developments in the economy, while one-month-ahead uncertainty can be driven by transitory events with limited material impact on the macroeconomy.

[21] Choi (2013) documented that the macroeconomic effect of uncertainty shocks differs between these two subperiods.

[22] We acknolwdge an anonymous referee for suggesting this exercise.

[23] The statistical significance of the results using the EPU index may be relatively weaker compared to the baseline. However, this finding aligns with the results presented in Bae et al. (2023) for our sample period. They demonstrate that, after 2008, the EPU index, unlike other popular uncertainty measures considered in our study, did not have any significant effect on the U.S. economy.

measure for three selected horizons (12, 24, and 36 months). For this exercise, we include inequality measures in level, as an effort to facilitate a comparison with the related studies.

Table 1. Forecast error variance decomposition of inequality

		JLN financial			JLN macro		
		H=12	H=24	H=36	H=12	H=24	H=36
Market income	Overall	0.24%	1.99%	4.06%	0.72%	5.40%	10.83%
	Upper	3.44%	4.31%	4.20%	5.64%	8.27%	8.96%
	Lower	9.37%	18.07%	21.79%	20.39%	39.05%	46.62%
		H=12	H=24	H=36	H=12	H=24	H=36
Labor income	Overall	2.53%	9.45%	14.30%	8.28%	20.93%	29.20%
	Upper	3.73%	4.30%	3.81%	2.83%	4.73%	4.65%
	Lower	11.15%	21.30%	25.00%	24.44%	42.51%	49.10%
		H=12	H=24	H=36	H=12	H=24	H=36
Non-labor income	Overall	1.75%	5.71%	8.75%	3.41%	7.10%	9.80%
	Upper	1.11%	4.79%	8.57%	2.22%	9.06%	14.80%
	Lower	1.33%	2.09%	1.85%	1.39%	1.04%	1.87%
		H=12	H=24	H=36	H=12	H=24	H=36
Disposable income	Overall	0.14%	0.10%	0.20%	1.26%	0.87%	0.80%
	Upper	1.55%	1.44%	1.21%	4.96%	6.09%	5.93%
	Lower	1.97%	2.91%	3.09%	2.14%	4.62%	6.86%
		H=12	H=24	H=36	H=12	H=24	H=36
Wealth	Top 10%	0.39%	0.35%	0.25%	0.10%	0.15%	0.25%
	Top 1%	1.90%	1.81%	1.56%	0.43%	0.84%	0.79%
	Top 0.1%	3.77%	3.69%	3.23%	0.57%	1.00%	0.85%
	Top 0.01%	4.54%	4.07%	3.29%	0.62%	0.82%	0.68%

Note: The top panel of the table shows the forecast error variance decomposition of the market income inequality explained by uncertainty shocks over the three forecasting horizons. (H=12, 24, and 36 months). The second, third, and fourth panels show the forecast error variance decomposition of the labor income inequality, non-labor income inequality, and disposable income inequality, respectively. The bottom panel of the table shows the forecast error variance decomposition of wealth inequality. The sample period is January 1976 to December 2019.

Overall, uncertainty shocks explain a non-trivial share of the variance in inequality measures after three years, but there also exists substantial heterogeneity across the distribution and the type of income as in the IRF analysis. For market income and labor income, uncertainty shocks explain a much larger share of variation in lower inequality than in upper inequality. However, this pattern is reversed for non-labor income inequality, reflecting its qualitatively different IRFs to uncertainty shocks in Figure 3. On average, macroeconomic uncertainty shocks explain a somewhat larger share of variation in most inequality measures than financial uncertainty shocks.

Figure C.4 in the online appendix presents the historical decomposition of inequality measures explained by uncertainty shocks. The role of uncertainty shocks in explaining income inequality varies across income definitions, inequality metrics, and sources of uncertainty. For example, during the period surrounding the Great Recession, changes in inequality, especially labor income inequality between the middle and poor, and non-labor income inequality between the rich and the middle, are particularly well explained by uncertainty shocks. This aligns with the narrative of the Great Recession, marked by heightened uncertainty, stock market collapse, and sluggish labor market recovery. For more detailed explanations of historical decomposition exercises, refer to Section C in the online appendix.

C. Uncertainty shocks and wealth inequality

Existing studies on uncertainty and inequality have mainly focused on income or consumption inequality due to the lack of high-frequency disaggregated wealth data. However, the level of concentration in wealth distribution is much higher than that of income distribution, and its cyclical fluctuations may not align with income inequality, warranting a separate analysis. Moreover, asset composition across households varies significantly. Financial wealth is highly concentrated among the rich and is sensitive to changes in financial market conditions or monetary policy. On the other hand, housing wealth constitutes a significant portion of middle-income households' assets and tends to respond more sluggishly. Additionally, poor households often lack significant net wealth, with the bottom 50% of the sample having close to zero or even negative wealth (i.e., debts exceeding assets), which has led us to consider a separate measure of wealth inequality (i.e., the wealth share of the rich) distinct from income inequality in our analysis.

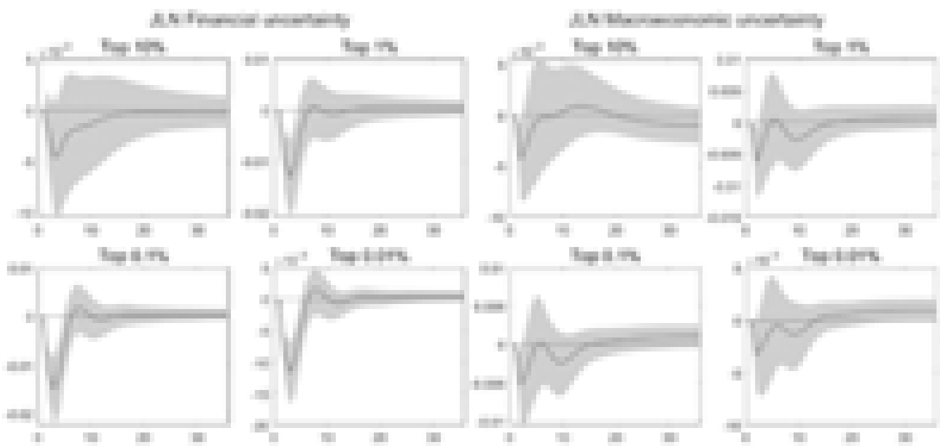
In previous literature, Mumtaz and Theophilopoulou (2017) show that expansionary monetary policy shocks reduce disposable income and consumption inequality in the United Kingdom. However, their later study (Mumtaz and Theophilopoulou, 2020) finds that monetary easing increases wealth inequality, suggesting that uncertainty shocks may have distinct distributional implications for income and wealth.[24]

To explore this possibility, we examine the impact of uncertainty shocks on wealth inequality using a VAR model, replacing income inequality with wealth inequality measures. Figure 5 displays the responses of wealth inequality to uncertainty shocks. In contrast to income inequality responses,

[24] Our study's advantage lies in using a common sample that allows for a direct comparison between income and wealth inequality, unlike previous research, which faced limitations due to shorter and non-overlapping sample periods for wealth inequality (2006–2018) compared to income inequality (1969–2012). This advantage strengthens the robustness of our conclusions and enhances the validity of the comparison between the distributional implications of uncertainty shocks on income and wealth.

the baseline wealth inequality shows a decrease, although statistically insignificant. However, focusing on even richer households, including the "super-rich" (top 1% or above), reveals a more substantial decline in wealth inequality, consistent with their disproportionate financial asset holdings (Hubmer et al., 2021) and the sharp decline in returns on risky assets, as shown in Figure 2.[25] The effects of macroeconomic uncertainty shocks are relatively smaller and less precisely estimated, attributed to the stronger link between financial uncertainty and asset prices compared to macroeconomic uncertainty.

Figure 5. Response of wealth inequality to uncertainty shocks



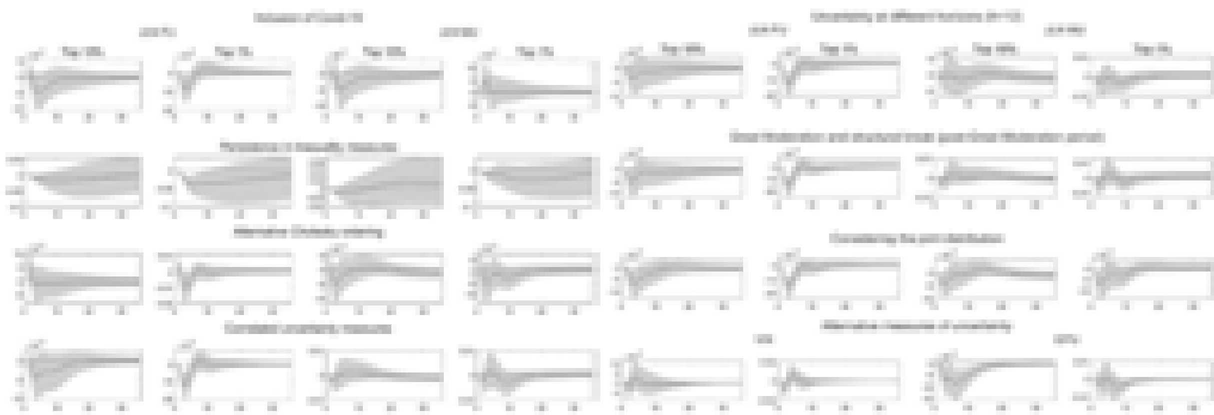
Note: This graph plots the 36-month-horizon IRFs of wealth shares to one standard deviation uncertainty shock. The shaded area represents the bootstrap 90% confidence interval. Each graph represents the response of the wealth share of different groups. The sample period is January 1976 to December 2019.

Robustness checks and additional exercises. In parallel with income inequality, we conduct a range of robustness checks on wealth inequality, summarized in Figure 6. Due to space limitations, we present the responses of the top 10% and 1% wealth shares, while those of the top 0.1% and 0.01% are available in Figures B.9 to B.16 in the online appendix. The responses of the top 0.1% and 0.01% are similar to the top 1%, supporting the main finding that financial uncertainty shocks reduce wealth concentration. However, the results for wealth inequality are less definitive compared to

[25] The portfolio rebalancing mechanism in Bayer et al. (2019) offers theoretical insight into the differential impact of uncertainty shocks on wealth-rich and wealth-poor households. Bayer et al. (2019) find that wealth-rich households hold a greater share of illiquid physical capital with higher returns during normal times, while wealth-poor households hold relatively more liquid assets. When household income uncertainty increases, the price and return on capital fall more sharply than returns on liquid assets, leading to greater losses for wealth-rich households. In contrast, wealth-poor households, despite holding less total wealth, are better insured and suffer less from lower capital returns due to their higher share of liquid assets. The correlation between household income uncertainty 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 captures both dimensions of uncertainty effectively.

income inequality. The primary conclusion that financial uncertainty shocks lower wealth concentration still holds, but the estimated responses to macroeconomic uncertainty are often statistically insignificant, aligning with the weaker impact of macroeconomic uncertainty shocks on risky asset prices.

Figure 6. Uncertainty shocks and wealth inequality: robustness checks



Note: This graph plots the 36-month-horizon IRFs of wealth inequality measures to one standard deviation uncertainty shock. The shaded area represents the bootstrap 90% confidence interval. Each row corresponds to different robustness checks outlined in Section III.B. To save space, we report only the results for the wealth share of the top 10% and the top 1% and delegate the rest of the results to Figures B.9. to B.16 in the online appendix.

Both types of uncertainty shocks generally lead to a similar qualitative impact on wealth inequality, with one exception when considering COVID-19, as shown in the first row of Figure 6 (details in Figure B.9 in the online appendix). In this case, macroeconomic uncertainty shocks increase the wealth concentration of the top 1% and above, reflecting the divergent paths of financial and macroeconomic uncertainty during the pandemic.[26]

In the forecast error variance decomposition of wealth inequality (bottom panel of Table 1), both types of uncertainty shocks have reduced roles compared to income inequality, particularly for macroeconomic uncertainty shocks. This could be attributed to differences between flow and stock variables and the short-term nature of high-frequency uncertainty shocks. The historical decomposition results in Figure C.5 in the online appendix also show a limited role of uncertainty shocks in explaining fluctuations in wealth inequality. Nevertheless, the importance of uncertainty

[26] Both financial and macroeconomic uncertainty surged during the COVID-19 outbreak, but their subsequent paths differed. Initially, heightened financial uncertainty adversely affected the rich and risky asset prices, such as stocks. However, asset prices rebounded rapidly due to accommodative monetary policies, leading to a resolution of financial uncertainty, despite ongoing uncertainty about the macroeconomic trajectory and pandemic-related policy measures. Altig et al. (2020) reported similar patterns using the VIX and EPU index on a weekly basis for the same period.

shocks tends to increase in both FEVD and historical decomposition when focusing on the richer groups, which are typically not included in previous studies.

D. Channels for uncertainty-inequality relationship

To ensure a comprehensive analysis of the channel through which uncertainty shocks affect income and wealth inequality and address any remaining concerns regarding omitted variable bias, we extend the baseline model. This larger-scale model includes additional variables that correspond to suggested channels through which uncertainty shocks affect inequality. By considering distinct effects on labor income, non-labor income, disposable income inequality, and wealth inequality documented before, we carefully select the additional variables. and aim to provide a more complete understanding of the distributional consequences of uncertainty shocks.

Specifically, we include wages and hours worked to examine the labor market response in greater detail. To account for interest income, we add 10-year treasury yields. Personal dividend income serves as a proxy for business income. Housing prices are included to contrast with financial wealth, which is primarily owned by wealthy households. Additionally, we explore the role of redistribution policy by adding personal transfer receipts to test its effect on reducing disposable income inequality following uncertainty shocks.[27] All nominal variables except for interest rates are deflated using the CPI.

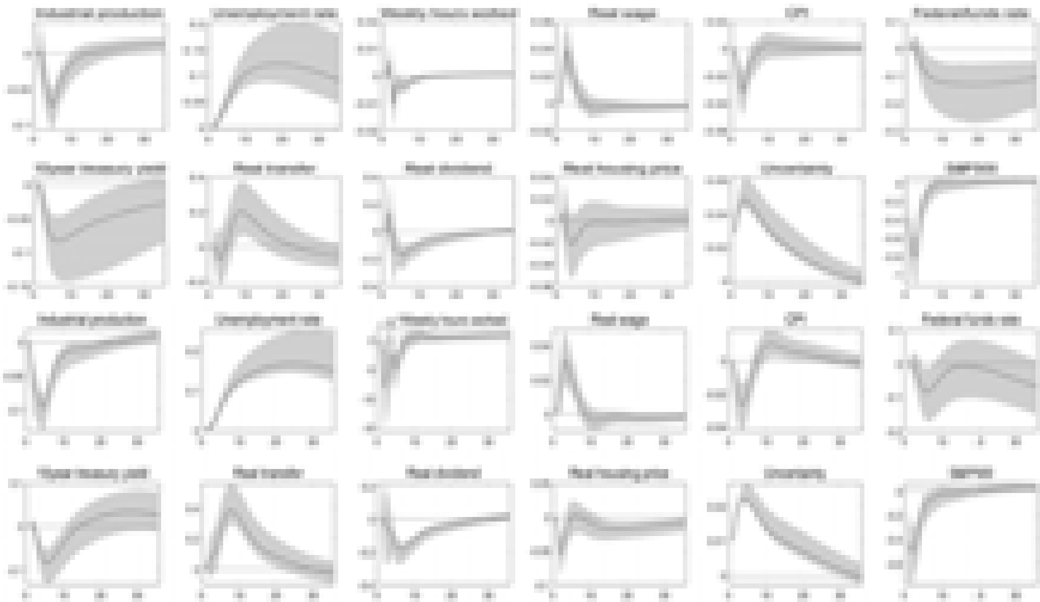
Figure 7 presents the responses of aggregate variables, validating the economic mechanisms underlying the distributional consequences of uncertainty shocks highlighted in Figures 3 and 5.[28] In addition to the variables in the baseline model, we find that uncertainty shocks lead to an increase in real wages and real personal transfers, while average hours worked, real dividend income, and real housing prices decrease. The rise in real wages aligns with recent research by Born and Pfeifer (2021). Combined with a steady increase in unemployment, the higher real wages suggest that uncertainty shocks disproportionately affect low-wage workers, who are more likely to face

[27] The corresponding Cholesky ordering is industrial production, the unemployment rate, the CPI, real wages, weekly hours worked, the federal funds rate (with Wu-Xia shadow rate), 10-year treasury yields, real personal transfers, real dividends, real housing prices, each inequality measure, the uncertainty index, and real S&P500. Non-stationary variables are first-differenced to ensure the stationarity of the VAR system. See Table A.2 in the online appendix for further details.

[28] Figures B.17 and B.18 in the online appendix show the responses of income inequality and wealth inequality in the lager-scale VAR model, respectively.

unemployment and therefore cannot benefit from the higher real wages for those who remain employed.[29] This finding helps explain the significant increase in lower labor income inequality.

Figure 7. Response of aggregate variables to uncertainty shocks: larger-scale VAR model



Note: This graph plots 36-month-horizon IRFs of macroeconomic variables to the one standard deviation uncertainty shock in a larger-scale VAR model (top: financial, bottom: macroeconomic). The Cholesky ordering is industrial production, the unemployment rate, weekly hours worked, real wages, CPI, federal funds rate (with Wu-Xia shadow rate), 10-year treasury yields, real personal transfers, real dividends, real housing prices, overall market income inequality, the uncertainty index, and real S&P500. The shaded area is the bootstrap 90% confidence interval. The sample period is January 1976 to December 2019.

Long-term interest rates experience a significant decline, leading to a reduction in interest income. The decline in real dividend income is consistent with findings in Bayer et al. (2019) and Alfaro et al. (forthcoming). Given that these forms of income are primarily concentrated among rich households, this can explain the pronounced decrease in upper non-labor income inequality. Moreover, an increase in transfers provides support for our explanation of the decline in disposable income inequality. As observed by Strobel et al. (2020), real housing prices also decrease following the uncertainty shock. However, this decline in housing prices is much smaller compared to the decline in stock prices and is statistically insignificant for financial uncertainty shocks. The fact that financial assets are more concentrated among wealthier households than housing assets can account for the reduction in top wealth concentration after uncertainty shocks.

[29] In the U.S. economy, a significant proportion of cyclical changes in total hours is attributed to the hours worked by lower-wage workers (Solon et al., 1994).

IV. Conclusion

Using newly available high-frequency data on income and wealth distribution in the U.S. economy, we conducted a comprehensive analysis of how different types of uncertainty shocks impact income and wealth inequality. Our findings reveal that uncertainty shocks have heterogeneous effects on different income and wealth groups, which cannot be simply summarized by a single metric of inequality. While overall income inequality may show limited change after uncertainty shocks, closer examination reveals significant decreases in inequality at the top and notable increases at the bottom of the distribution. This underscores the importance of considering the entire distribution to avoid misleading interpretations of the distributional effects of uncertainty shocks.

Furthermore, the definitions of income also play a crucial role in shaping the uncertainty-income inequality relationship. We observed distinct responses in labor income inequality compared to non-labor income inequality, suggesting different transmission channels for each income component. However, when disposable income is taken into account, uncertainty shocks lead to reduced income inequality, suggesting that redistribution policies effectively mitigate the negative distributional impacts of uncertainty shocks. Additionally, uncertainty shocks tend to reduce top wealth concentration, primarily through a decline in financial asset prices. While housing prices also decrease, their impact is considerably smaller than that of stock prices, thereby mitigating the adverse effects on the wealth share of the middle class. Overall, our study provides a comprehensive understanding of how uncertainty shocks affect income and wealth distribution, highlighting the need to consider different dimensions of inequality and various sources of uncertainty for a more nuanced analysis of their distributional consequences.

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

Sangyup Choi[†] Jeeyeon Phi[‡]
Yonsei University Yonsei University

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This online appendix contains a detailed description of data (Section A), robustness checks of the key findings (Section B), and results of additional exercises (Section C).

A. Description of data

Measures of inequality. Blanchet et al. (2022) adopt a method that involves taking a moving average of distributional national accounts annual microdata and rescaling each income and wealth component to monthly data. This approach is well-suited for non-labor income parts, where short-term gross changes largely capture distributional changes for each component. However, labor income, which constitutes approximately 75% of the national income, can undergo rapid changes in distribution due to fluctuations in employment and wage earnings across different industries and counties. To account for these fast-moving distributions, monthly employment data and quarterly specific wage distributions from the BLS Quarterly Census of Employment and Wages are utilized.

In this study, the baseline income inequality measure is based on household market income, which encompasses all capital and labor income before taxation, constituting the national income. Market income is then decomposed into labor income and non-labor income, allowing for an understanding of the differential responses of upper and lower inequality to uncertainty shocks. Additionally, disposable income is considered to explore the interplay between uncertainty shocks and redistribution policies. For the wealth inequality measure, all marketable wealth held by households is used, with funded pensions included and debts subtracted. Vehicles and unfunded pension promises are excluded from the wealth data. A complete description of the data construction process using publicly available data can be found in Blanchet et al. (2022).

[†] School of Economics, Yonsei University, 50 Yonsei-ro, Seodaemun-gu, Seoul 03722, South Korea. Email address: sangyupchoi@yonsei.ac.kr.
[‡] School of Economics, Yonsei University, 50 Yonsei-ro, Seodaemun-gu, Seoul 03722, South Korea. Email address: jeeyeonphi@yonsei.ac.kr.

Figure A.1. Evolution of income shares of different groups

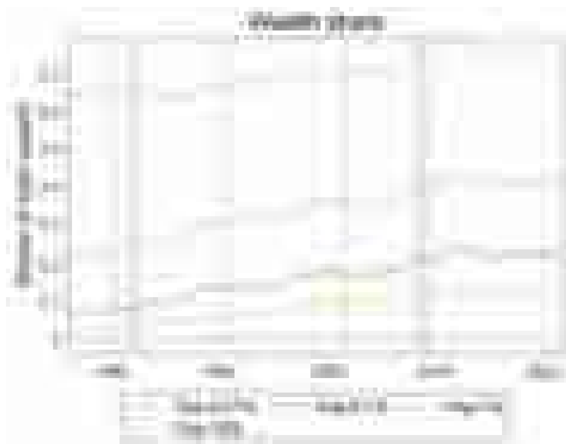
Note: The top panel plots the share of market income (left) and labor income (right) across different groups, while the bottom panel plots the share of non-labor income (left) and disposable income (right). The sample period is January 1976 to December 2021. Shaded areas denote NBER recession dates.

The top panel of Figure A.1 displays the share of market income (left) and labor income (right), while the bottom panel exhibits the share of non-labor income (left) and disposable income (right) for each group from 1976M1 to 2021M12. The share of each group is calculated as its total income relative to the total income of the working-age population, with the income share of the top 10%, middle 40%, and bottom 50% adding up to one. These income shares collectively represent the overall inequality level of the economy, providing a comprehensive picture not captured by a single-statistic measure like the Gini index. Changes in income shares reveal how different income groups have fared compared to others over time.

Over the sample period, there has been a prominent trend of increasing inequality in all income categories, evident from the growth in income shares of the top 10%, 1%, 0.1%, and 0.01%. This aligns with prior observations that U.S. inequality has intensified since the 1980s (Piketty et al., 2018). Non-labor income inequality surpasses labor income inequality and has exhibited a faster growth rate, which underscores the importance of our decomposition exercises. Relative income shares tend to fluctuate across business cycles, and during recessions, especially the recent pandemic, the market income share of top income groups tends to decline.

Figure A.2 illustrates the relative wealth shares of top wealth groups over time. The computation of the wealth share for each group follows the same methodology as the income share. The data clearly show a notable increase in the wealth share of the rich over the past 45 years, particularly for those situated at the right tail of the distribution. Due to this trend, we examine the response of the wealth share of these specific groups, in addition to the baseline (top 10% wealth share), to further explore the distributional consequences of uncertainty shocks.

Figure A.2. Evolution of wealth shares of different groups



Note: This graph plots the share of wealth across different groups. The sample period is January 1976 to December 2021. Shaded areas denote NBER recession dates.

Measures of uncertainty. The JLN uncertainty indices (Jurado et al., 2015), utilized in our baseline analysis and widely employed in subsequent studies, are preferred due to their model-independent nature. The authors emphasize that economic decision-making hinges on the predictability of the economy, not simly the variability of specific economic indicators. The financial (macroeconomic) uncertainty index is calculated by aggregating the individual uncertainty in the respective financial (macroeconomic) variables. Individual uncertainty is derived by isolating the unforecastable component's conditional volatility in the future while 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 financial 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:

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

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:

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

Jurado et al. (2015) used 147 monthly financial time series to construct JLN financial uncertainty.[30] The JLN macroeconomic uncertainty U_t^M is constructed in the same way, but using 134 monthly macroeconomic time series.[31] We use one-month ahead (h=1) uncertainty as our baseline measure of uncertainty, but the key results still hold when using one-year (h=12) ahead uncertainty.

Table A.1. Correlation matrix for the uncertainty measures

	JLN FU	JLN MU	VIX	EPU
JLN FU	1			
JLN MU	0.577	1		
VIX	0.819	0.594	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.

[30] 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.

[31] 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.

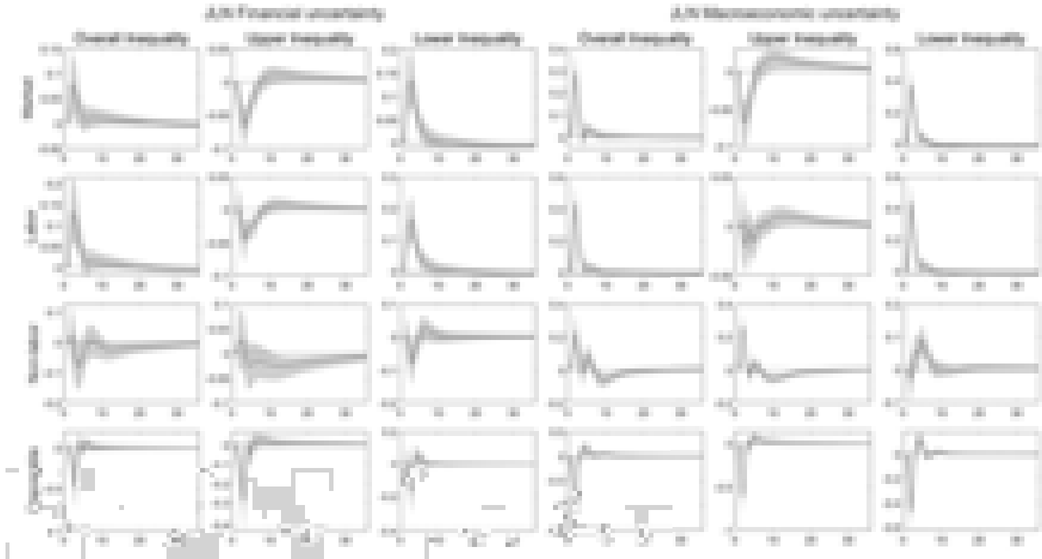
Table A.2. Augmented Dickey-Fuller stationarity test results

	p-values	
	Level	First difference
Industrial production (logged)	0.44	0.00
Unemployment rate	0.04	0.00
CPI (logged)	0.00	0.02
Federal funds rate (with Wu-Xia shadow rate)	0.01	0.00
Financial uncertainty	0.00	0.00
Macroeconomic uncertainty	0.02	0.00
S&P 500 (logged)	0.87	0.00
Weekly hours worked	0.10	0.00
Real wages (logged)	0.95	0.00
10-year treasury yields	0.06	0.00
Real personal transfer (logged)	0.94	0.00
Real personal dividend income (logged)	0.93	0.00
Real housing prices (logged)	0.47	0.03
Overall market income inequality (logged)	0.35	0.00
Overall labor income inequality (logged)	0.25	0.00
Overall non-labor income inequality (logged)	0.84	0.00
Overall disposable income inequality (logged)	0.10	0.00
Top 10% wealth share	0.77	0.00
Top 1% wealth share	0.61	0.00
Top 0.1% wealth share	0.58	0.00
Top 0.01% wealth share	0.68	0.00

Note: This table shows the p-values of the augmented Dickey-Fuller test. The lag length is selected automatically by the Schwarz criterion with 18 maximum lags. The sample period is January 1976 to December 2019.

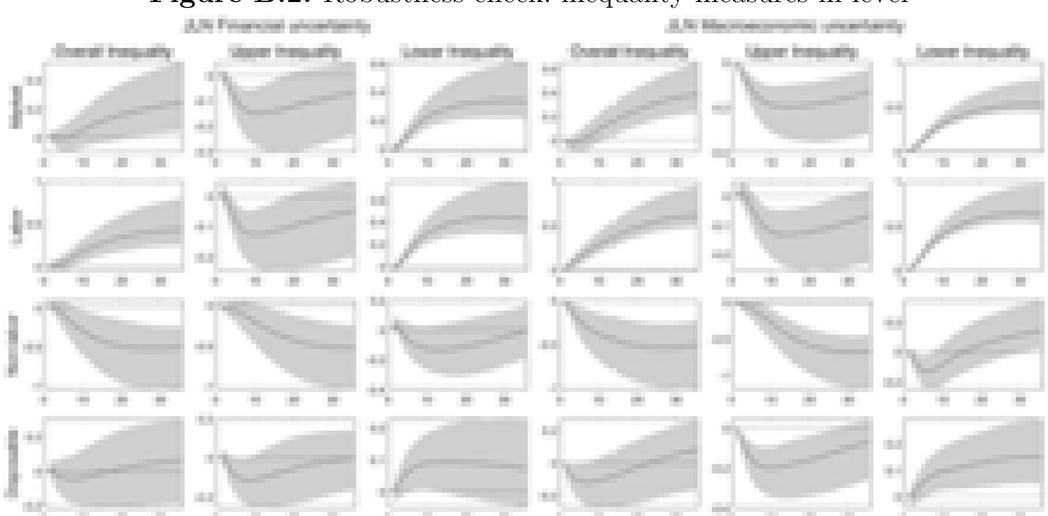
B. Robustness checks

Figure B.1. Robustness check: including COVID-19



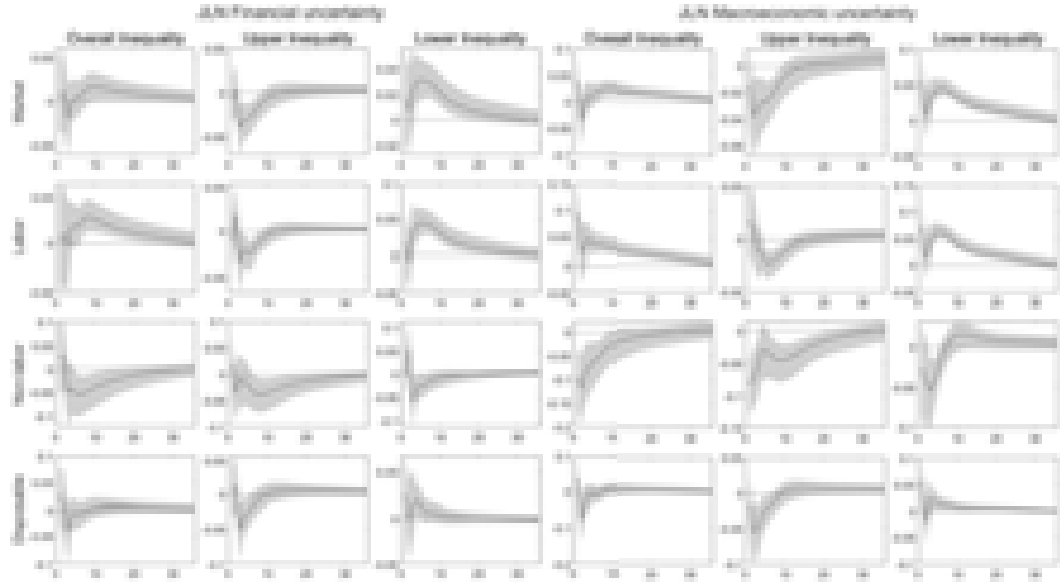
Note: This graph plots the 36-month-horizon IRFs of various income inequality measures to one standard deviation uncertainty shock. The shaded area represents the bootstrap 90% confidence interval. Each row represents different income definitions and each column represents different inequality metrics and different uncertainty measures. The sample period is January 1976 to December 2021.

Figure B.2. Robustness check: inequality measures in level



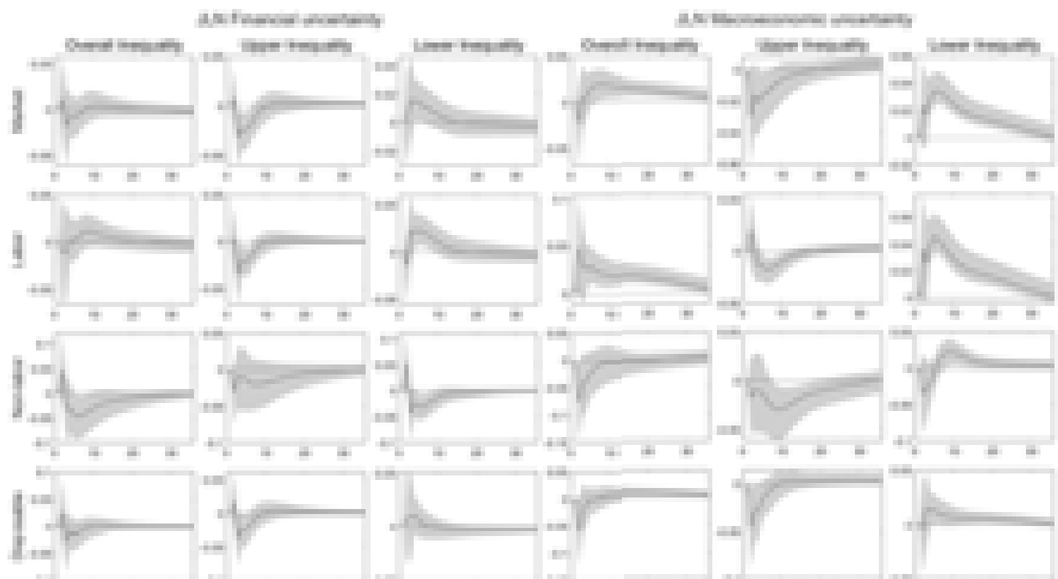
Note: This graph plots the 36-month-horizon IRFs of various income inequality measures to one standard deviation uncertainty shock. Inequality measures are included in level. The shaded area represents the bootstrap 90% confidence interval. Each row represents different income definitions and each column represents different inequality metrics in level and different uncertainty measures. The sample period is January 1976 to December 2019.

Figure B.3. Robustness check: alternative Cholesky ordering



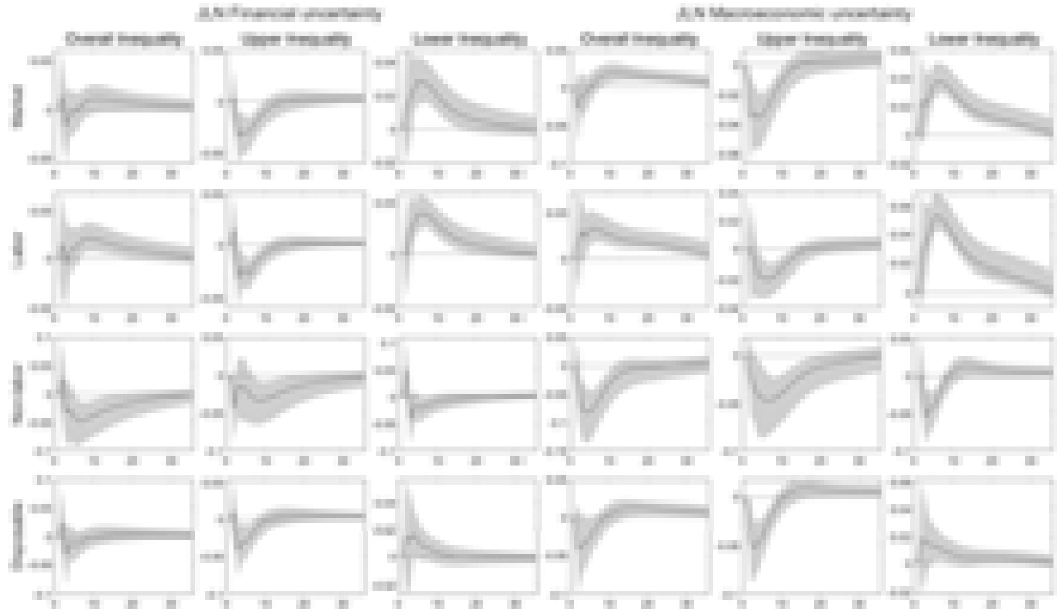
Note: This graph plots the 36-month-horizon IRFs of various income inequality measures to one standard deviation uncertainty shock. The alternative Cholesky ordering mostly follows Bloom (2009): S&P500, uncertainty index, federal funds rate (with the Wu-Xia shadow rate, CPI, unemployment rate, industrial production, and inequality measure. The shaded area represents the bootstrap 90% confidence interval. Each row represents different income definitions and each column represents different inequality metrics and different uncertainty measures. The sample period is January 1976 to December 2019.

Figure B.4. Robustness check: correlated uncertainty measures



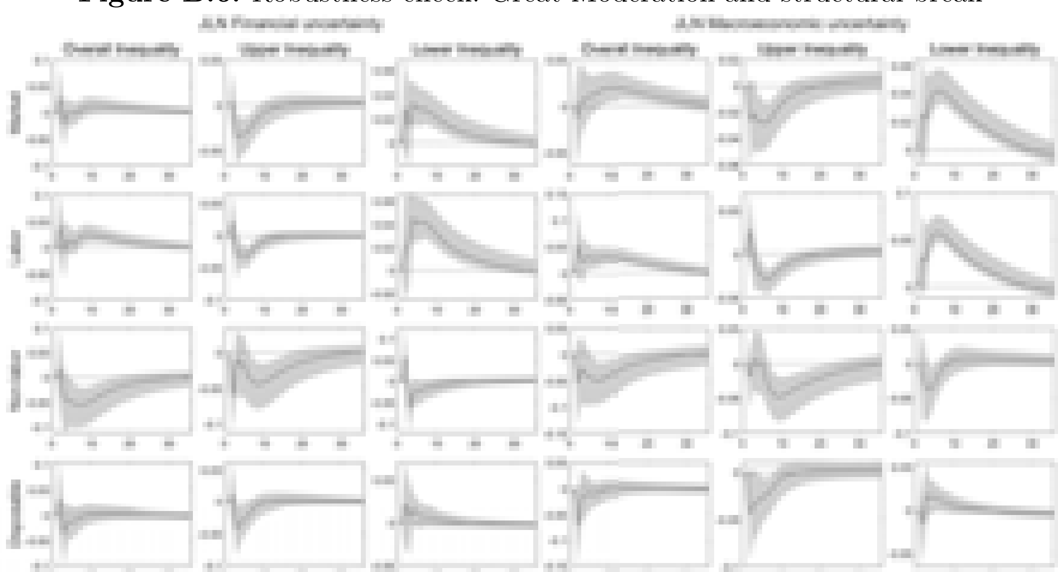
Note: This graph plots the 36-month-horizon IRFs of various income inequality measures to one standard deviation uncertainty shock. Both types of uncertainty measures are included in the VAR system simultaneously. The shaded area represents the bootstrap 90% confidence interval. Each row represents different income definitions and each column represents different inequality metrics and different uncertainty measures. The sample period is January 1976 to December 2019.

Figure B.5. Robustness check: uncertainty at different horizons (h=12)



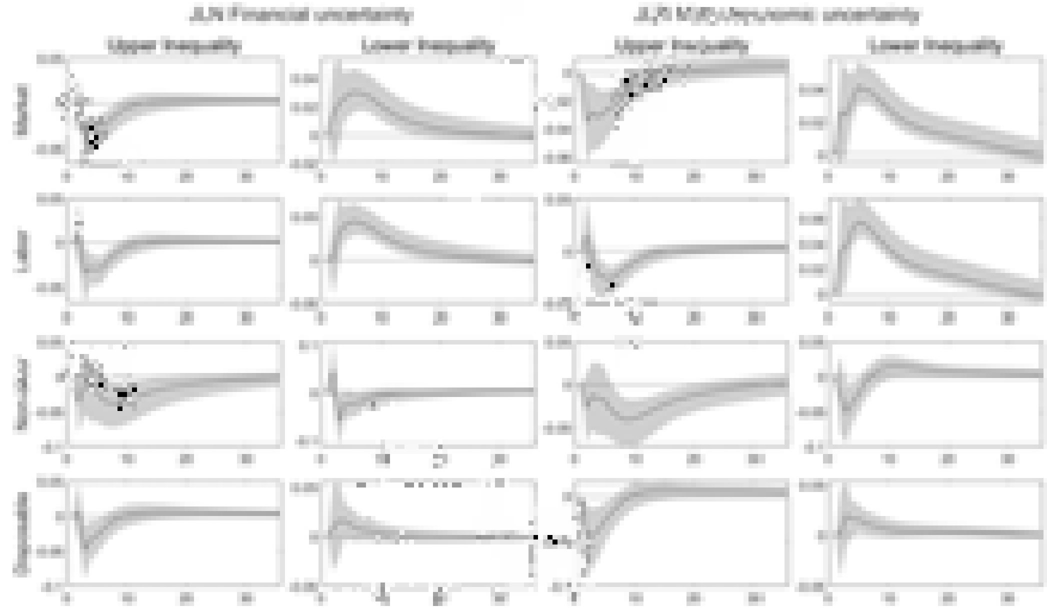
Note: This graph plots the 36-month-horizon IRFs of various income inequality measures to one standard deviation uncertainty shock. One-year-ahead uncertainty (h=12) is used instead. The shaded area represents the bootstrap 90% confidence interval. Each row represents different income definitions and each column represents different inequality metrics and different uncertainty measures. The sample period is January 1976 to December 2019.

Figure B.6. Robustness check: Great Moderation and structural break



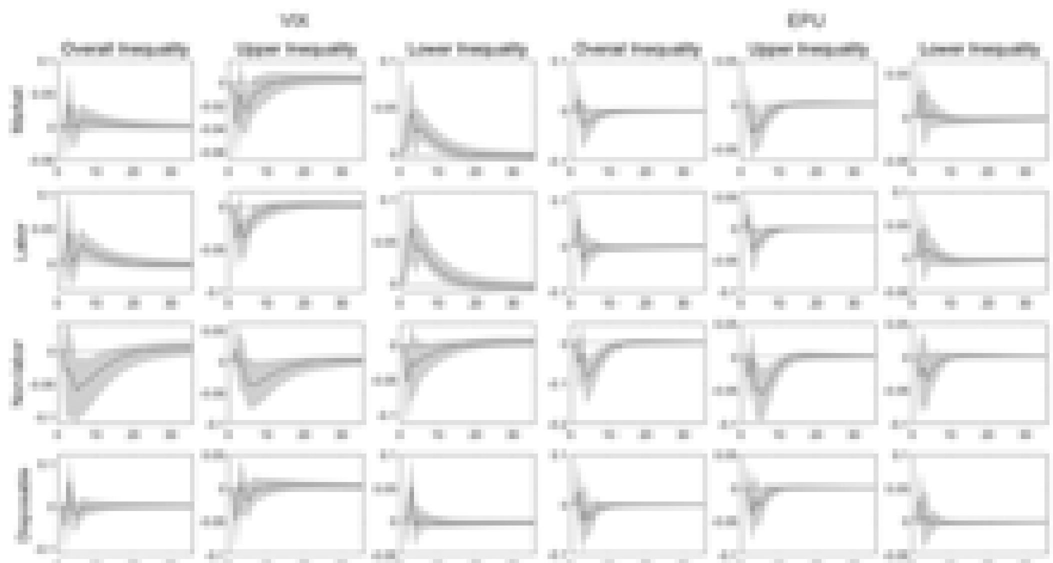
Note: This graph plots the 36-month-horizon IRFs of various income inequality measures to one standard deviation uncertainty shock. The shaded area represents the bootstrap 90% confidence interval. Each row represents different income definitions and each column represents different inequality metrics and different uncertainty measures. The sample period is January 1984 to December 2019.

Figure B.7. Robustness check: considering the entire distribution simultaneously



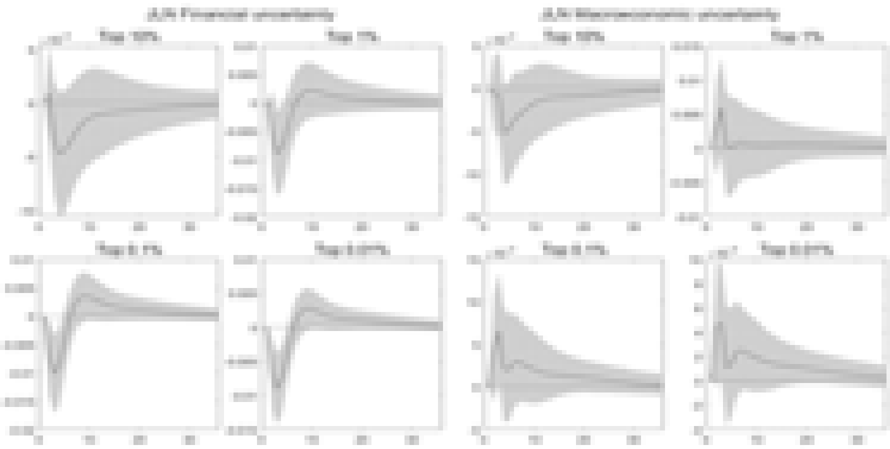
Note: This graph plots the 36-month-horizon IRFs of various income inequality measures to one standard deviation uncertainty shock. Both upper and lower inequality measures are included in the same VAR system. The shaded area represents the bootstrap 90% confidence interval. Each row represents different income definitions and each column represents different inequality metrics and different uncertainty measures. The sample period is January 1976 to December 2019.

Figure B.8. Robustness check: alternative measures of uncertainty



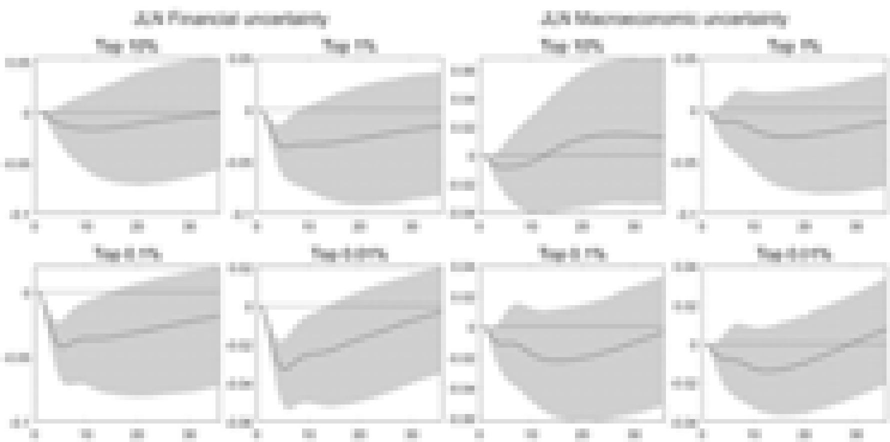
Note: This graph plots the 36-month-horizon IRFs of various income inequality measures to one standard deviation uncertainty shock. The VIX (EPU) index is used instead of JLN financial uncertainty (macroeconomic uncertainty). The shaded area represents the bootstrap 90% confidence interval. Each row represents different income definitions and each column represents different inequality metrics and different uncertainty measures. The sample period is January 1976 to December 2019.

Figure B.9. Robustness check: including COVID-19



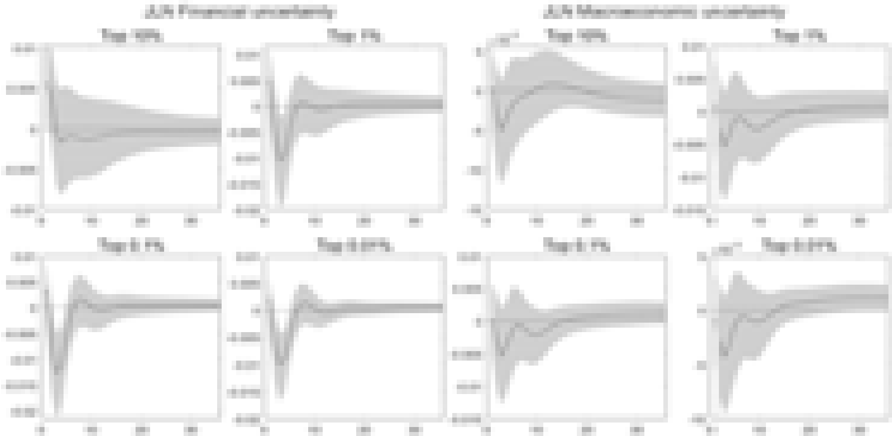
Note: This graph plots the 36-month-horizon IRFs of wealth shares to one standard deviation uncertainty shock. The shaded area represents the bootstrap 90% confidence interval. Each graph represents the response of the wealth share of different groups. The sample period is January 1976 to December 2021.

Figure B.10. Robustness check: inequality measures in level



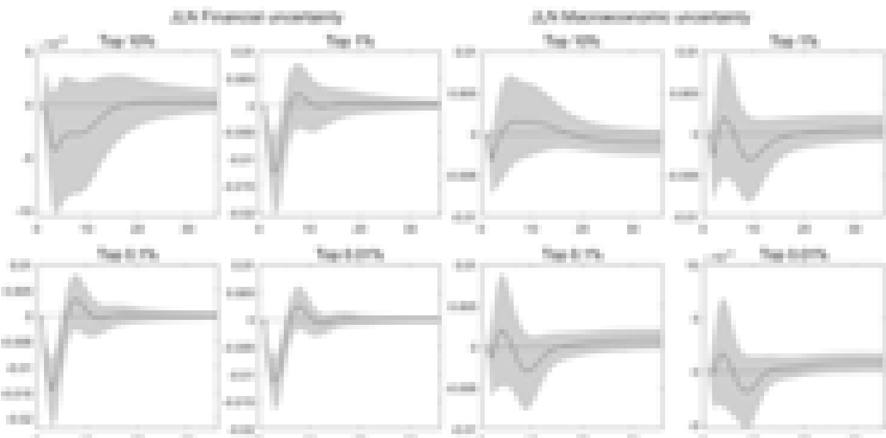
Note: This graph plots the 36-month-horizon IRFs of wealth shares to one standard deviation uncertainty shock. Wealth inequality measures are included in level. The shaded area represents the bootstrap 90% confidence interval. Each graph represents the response of the wealth share of different groups in level. The sample period is January 1976 to December 2019.

Figure B.11. Robustness check: alternative Cholesky ordering



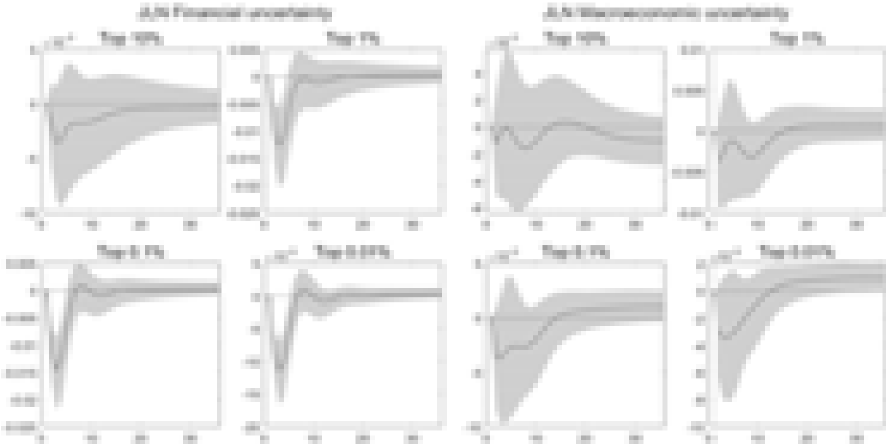
Note: This graph plots the 36-month-horizon IRFs of wealth shares to one standard deviation uncertainty shock. The Cholesky ordering mostly follows Bloom (2009): S&P500, uncertainty index, federal funds rate (with the Wu-Xia shadow rate, CPI, unemployment rate, industrial production, and inequality measure. The shaded area represents the bootstrap 90% confidence interval. Each graph represents the response of the wealth share of different groups. The sample period is January 1976 to December 2019.

Figure B.12. Robustness check: correlated uncertainty measures



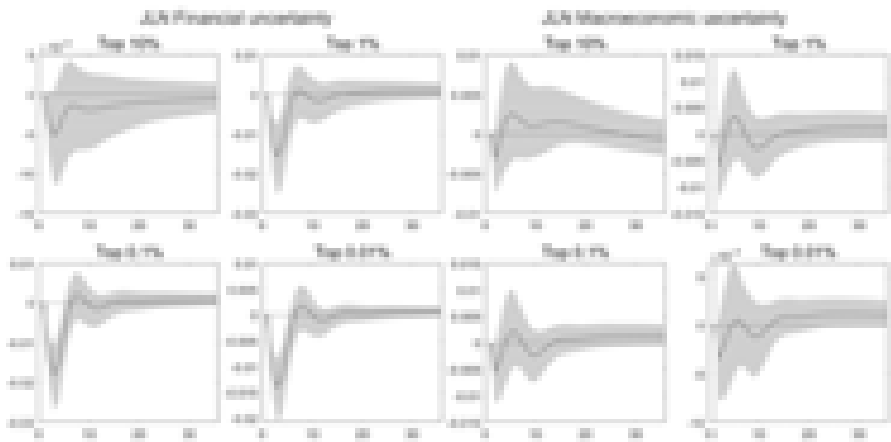
Note: This graph plots the 36-month-horizon IRFs of wealth shares to one standard deviation uncertainty shock. Both types of uncertainty measures are included in the VAR system simultaneously. The shaded area represents the bootstrap 90% confidence interval. Each graph represents the response of the wealth share of different groups. The sample period is January 1976 to December 2019.

Figure B.13. Robustness: uncertainty at different horizons (*h=12*)



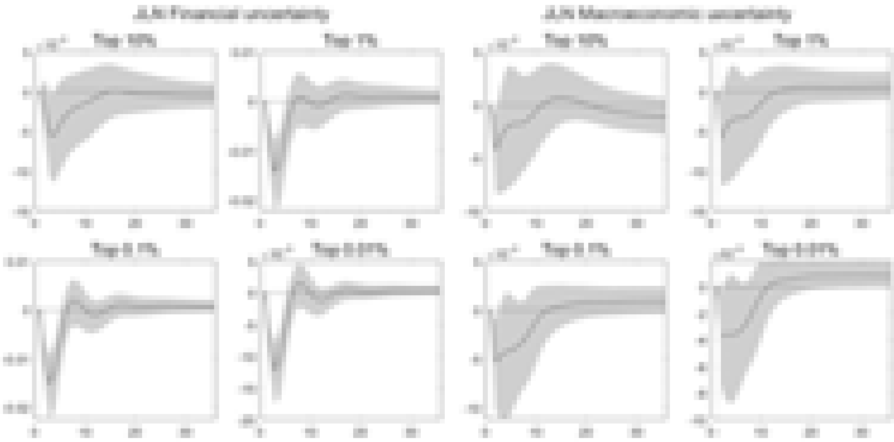
Note: This graph plots the 36-month-horizon IRFs of wealth shares to one standard deviation uncertainty shock. One-year-ahead uncertainty was used in the VAR system. The shaded area represents the bootstrap 90% confidence interval. Each graph represents the response of the wealth share of different groups. The sample period is January 1976 to December 2019.

Figure B.14. Robustness check: Great Moderation and structural break



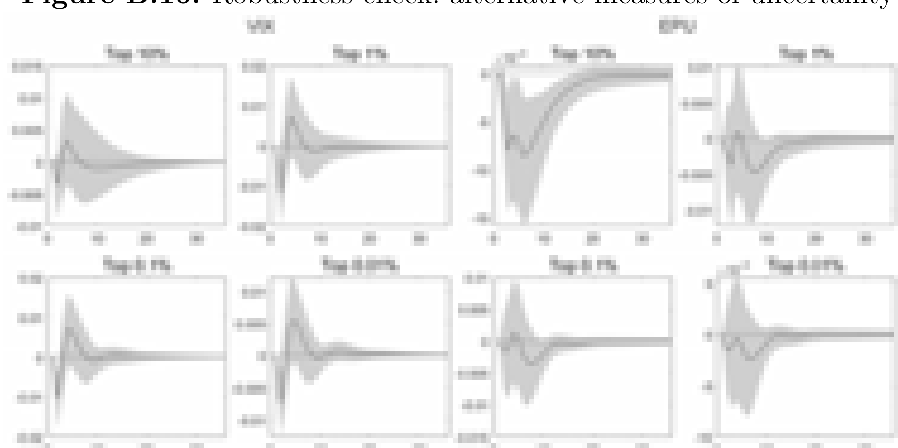
Note: This graph plots the 36-month-horizon IRFs of wealth shares to one standard deviation uncertainty shock. The shaded area represents the bootstrap 90% confidence interval. Each graph represents the response of the wealth share of different groups. The sample period is January 1984 to December 2019.

Figure B.15. Robustness check: considering the entire distribution simultaneously



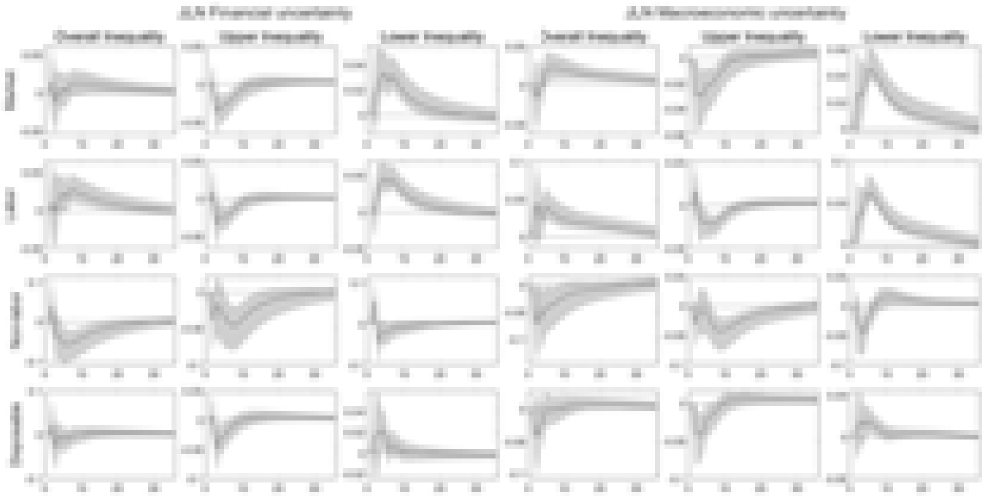
Note: This graph plots the 36-month-horizon IRFs of wealth shares to one standard deviation uncertainty shock. The wealth share of the top 10%, 1%, 0.1%, and 0.01% were all included in the same VAR system. The shaded area represents the bootstrap 90% confidence interval. Each graph represents the response of the wealth share of different groups. The sample period is January 1976 to December 2019.

Figure B.16. Robustness check: alternative measures of uncertainty



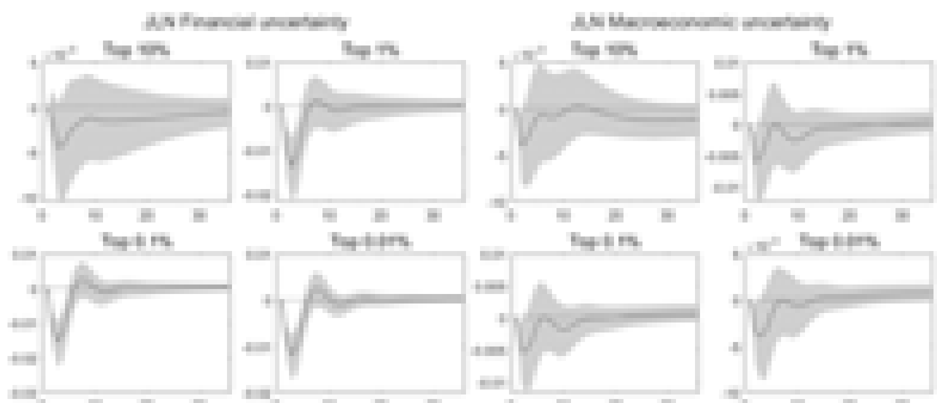
Note: This graph plots the 36-month-horizon IRFs of wealth shares to one standard deviation uncertainty shock. The VIX (EPU) index is used instead of JLN financial uncertainty (macroeconomic uncertainty). The shaded area represents the bootstrap 90% confidence interval. Each graph represents the response of the wealth share of different groups. The sample period is January 1976 to December 2019.

Figure B.17. Robustness check: income inequality in larger-scale VAR



Note: This graph plots 36-month-horizon IRFs of macroeconomic variables to the one standard deviation uncertainty shock in a larger-scale VAR model. The Cholesky ordering is industrial production, the unemployment rate, weekly hours worked, real wages, CPI, federal funds rate, with Wu-Xia shadow rate), 10-year treasury yields, real personal transfers, real dividends, real housing prices, an inequality measure, the uncertainty index, and real S&P500. The shaded area is the bootstrap 90% confidence interval. The sample period is January 1976 to December 2019.

Figure B.18. Robustness check: wealth inequality in larger-scale VAR



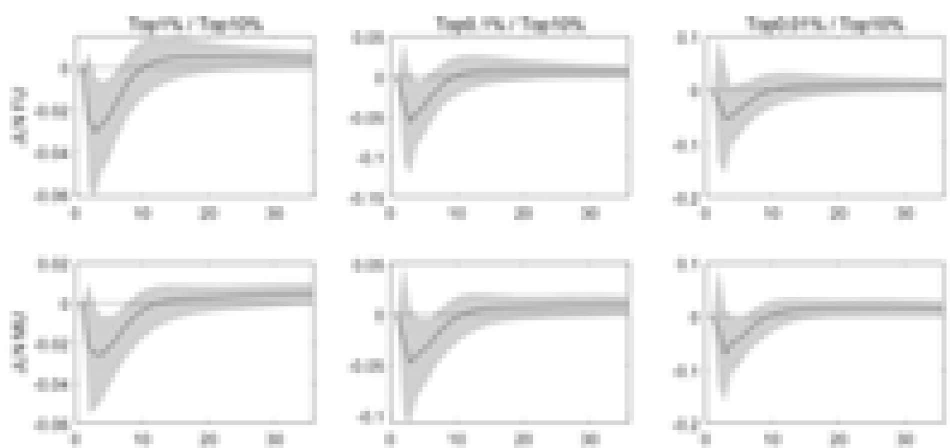
Note: This graph plots 36-month-horizon IRFs of macroeconomic variables to the one standard deviation uncertainty shock in a larger-scale VAR model. The Cholesky ordering is industrial production, the unemployment rate, weekly hours worked, real wages, CPI, federal funds rate, with Wu-Xia shadow rate), 10-year treasury yields, real personal transfers, real dividends, real housing prices, a wealth measure, the uncertainty index, and real S&P500. The shaded area is the bootstrap 90% confidence interval. The sample period is January 1976 to December 2019.

C. Additional exercises

This section presents supplementary exercises aimed at bolstering the interpretation of our main findings and elucidating underlying mechanisms. Each exercise is described in detail to provide a comprehensive understanding of its implementation and results.

Top income inequality and uncertainty. We examine the income distribution among wealthy households to gain insights into how uncertainty shocks impact income inequality within this group. Due to data limitations, we can only provide market income inequality for this analysis, without the ability to decompose it into labor and non-labor income. To facilitate comparison among affluent households, we introduce a top income inequality measure, represented as the ratio of the average income of the top 1% to the average income of the top 10%: $\frac{\bar{P}_{99,100}}{\bar{P}_{90,100}}$. Similar measures are computed for the top 0.1% and 0.01% income groups. Figure C.1 illustrates that uncertainty shocks have a more pronounced negative impact on the income of super-rich households compared to rich households, aligning with the income composition channel described in our study.

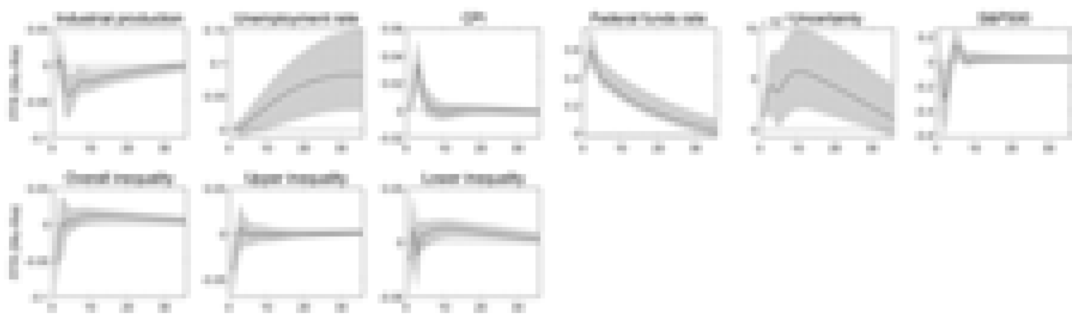
Figure C.1. Response of top income inequality to uncertainty shocks



Note: This graph plots the 36-month-horizon IRFs of various income inequality measures 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 different inequality metrics. The sample period is January 1976 to December 2019.

Comparison with monetary policy shocks. To gauge the economic significance of the uncertainty shocks depicted in Figure 3, we conduct an analysis of the effects of monetary policy shocks using the same VAR model. Monetary policy shocks are chosen for their ease of interpretation, as their size is straightforward to measure (e.g., a 25 basis point increase in the policy rate). Additionally, both the aggregate and distributional effects of monetary policy shocks are well-studied in the literature (e.g., Christiano et al., 1999; Coibion et al., 2017). Given that our VAR model already aligns with the standard timing assumption of the monetary VAR model (i.e., the federal funds rate is positioned after slow-moving macroeconomic variables like the unemployment rate and CPI, but before fast-moving financial variables such as stock returns), we utilize the baseline model for drawing inferences.

Figure C.2. The aggregate and distributional effects of monetary policy shocks



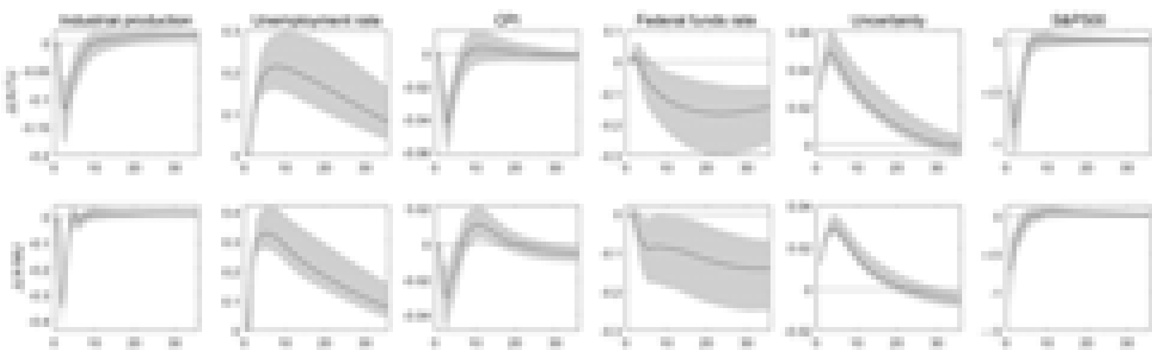
Note: This graph plots the 36-month-horizon impulse response functions to a 50 basis point monetary policy shock. Responses are expressed in percentage terms. The first row represents the response of aggregate variables. The second row represents the responses of market income inequality. The shaded area represents the bootstrap 90% confidence interval. The sample period is January 1976 to December 2019.

As anticipated, an exogenous tightening of 50 basis points in the federal funds rate leads to a decrease in output and stock returns, along with an increase in unemployment. We observe a notable increase in prices, leading to what is commonly referred to as a “price puzzle,” which is frequently observed in recursively-identified VAR models when additional variables like commodity prices are not included (e.g., Rusnák et al., 2013). However, our focus in this exercise is to assess the quantitative significance of uncertainty shocks in comparison to standard monetary policy shocks. As a result, we do not make further adjustments to address the price puzzle.

An exogenous monetary tightening results in an increase in overall income inequality, in line with the findings of Coibion et al. (2017). More notably, upper inequality experiences a short-term decrease of 0.04%, likely driven by lower business income, while lower inequality moderately increases by 0.02% in a more persistent manner, reflecting the adverse effects of monetary tightening on the labor market. Both of these effects are attributed to the economic slowdown caused by the monetary policy shock. Importantly, the magnitude of changes in both upper and lower inequality measures is quite similar to the effects of a one standard deviation increase in uncertainty shocks, as shown in the first row of Figure 3. Consequently, we can infer that the distributional consequences of uncertainty shocks, at one standard deviation, can be equated to approximately a 50 basis point exogenous monetary policy tightening, which holds considerable economic significance as a unit of structural shock.

COVID-19. We present the aggregate effects of uncertainty shocks in an extended sample up to 2021M1. The inclusion of COVID-19 in the analysis tends to amplify the adverse impact of uncertainty shocks on aggregate variables, particularly on output and unemployment. Additionally, the differences in magnitude between the two types of uncertainty shocks become more pronounced. Specifically, macroeconomic uncertainty shocks now exhibit a significantly larger effect on output and unemployment compared to financial uncertainty shocks, which helps explain the substantial increase in lower income inequality observed in the post-COVID-19 period compared to the pre-COVID-19 sample.

Figure C.3. The aggregate effects of uncertainty shocks: including COVID-19

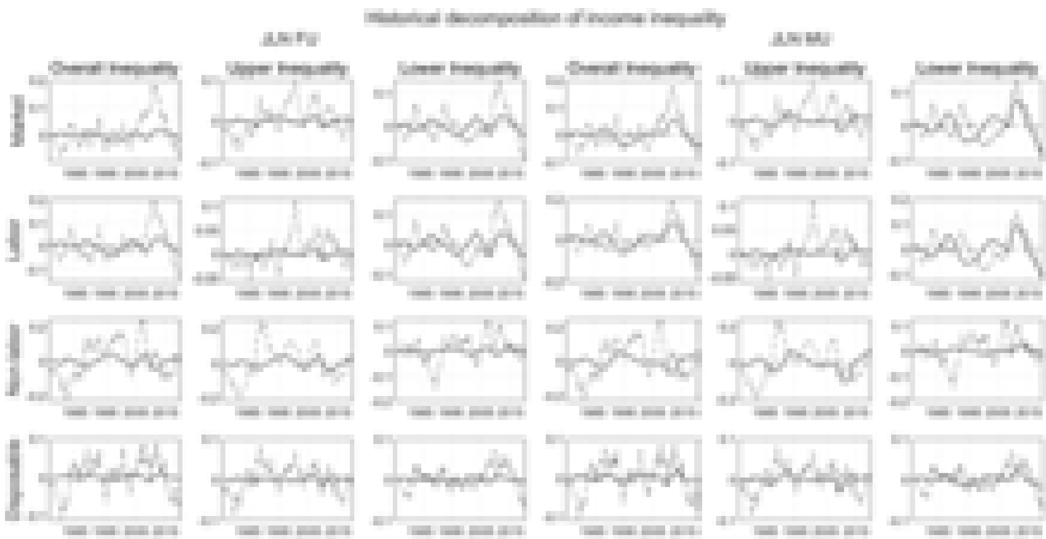


Note: This graph plots the 36-month-horizon impulse response functions of the aggregate variables to one standard deviation uncertainty shock. The shaded area represents the bootstrap 90% confidence interval. Each row represents different uncertainty measures and each column represents the responses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

Historical decomposition of inequality. We conduct a historical decomposition of income and wealth inequality measures to examine how the role of uncertainty shocks in explaining inequality evolves over time. Figure C.4 highlights distinct patterns in cyclical fluctuations among different inequality metrics and income definitions, which accounts for the varying quantitative impact of uncertainty shocks on these measures.

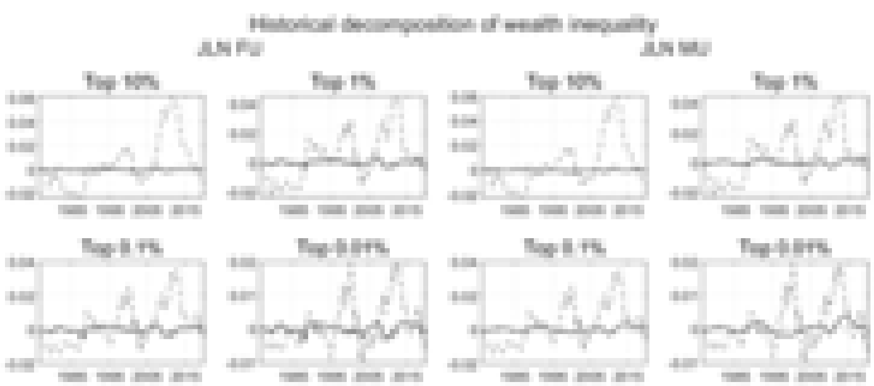
For example, during the Great Recession, market income inequality experienced a sharp increase, a result expected given the significant influence of heightened uncertainty during that period. Notably, uncertainty shocks appear to better explain changes in labor income inequality than non-labor income inequality. Moreover, within labor income inequality measures, uncertainty shocks play a prominent role in explaining the divergence between the middle and lower-income groups. Conversely, uncertainty shocks only contribute to minor fluctuations in top wealth concentration as shown in Figure C.5, consistent with the findings from the forecast error variance decomposition exercise presented in Table 1. These observations underscore the non-uniform role of uncertainty shocks across the income distribution and their varying impact on different aspects of inequality.

Figure C.4. Historical decomposition of income inequality



Note: This graph plots the historical decomposition of income inequality measures. Each row represents different income definitions and each column represents different inequality metrics and different uncertainty measures. The sample period is January 1976 to December 2019.

Figure C.5. Historical decomposition of wealth inequality



Note: This graph plots the historical decomposition of wealth shares. Each graph represents the historical decomposition of different wealth groups. The first two columns represent financial uncertainty, and the next columns represent macroeconomic uncertainty. The sample period is January 1976 to December 2019.

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