Business Cycles and Earnings Inequality

Byoungchan Lee

HKUST CEP Working Paper No. 2020-01

April 19, 2020

HKUST Center for Economic Policy
The Hong Kong University of Science and Technology
Clear Water Bay, Kowloon, Hong Kong
T: 3469 3007 E:cep@ust.hk W: cep.hkust.edu.hk

Business Cycles and Earnings Inequality

Byoungchan Lee

HKUST CEP Working Paper No. 2020-01
April 19, 2020

Abstract

I construct a novel, quarterly measure of earnings inequality and document the following facts. First, shocks to productivity and government expenditure have significant effects on earnings inequality, while monetary policy shocks have little effect. Second, unanticipated innovations in earnings inequality, summarizing redistributive forces from the bottom to the top, substantially lower aggregate demand in a U-shaped manner. Finally, the power of stabilization policies increases with the level of inequality. These empirical results are rationalized by a tractable two-agent model, featuring countercyclical earnings risk, an endogenous extensive margin of being credit constrained, and decreasing relative risk aversion preferences.

Author's contact information

Byoungchan Lee

Department of Economics, Hong Kong University of Science and Technology
Email: bclee@ust.hk

Business Cycles and Earnings Inequality

Byoungchan Lee*

Hong Kong University of Science and Technology

April 19, 2020

Abstract

I construct a novel, quarterly measure of earnings inequality and document the following facts. First, shocks to productivity and government expenditure have significant effects on earnings inequality, while monetary policy shocks have little effect. Second, unanticipated innovations in earnings inequality, summarizing redistributive forces from the bottom to the top, substantially lower aggregate demand in a U-shaped manner. Finally, the power of stabilization policies increases with the level of inequality. These empirical results are rationalized by a tractable two-agent model, featuring countercyclical earnings risk, an endogenous extensive margin of being credit constrained, and decreasing relative risk aversion preferences.

Keywords: business cycle, inequality, impulse response, forecast error variance decomposition, stabilization policy, marginal propensity to consume

JEL Codes: E32, E21, E52, E62, D31

---

*bclee@ust.hk. I am especially grateful to Yuriy Gorodnichenko for his continual support and invaluable guidance. Emmanuel Saez gave important advice on including, but not limited to, the construction of inequality measures. I also thank ChaeWon Baek, Saroj Bhattarai, Olivier Blanchard, Nicolas Caramp, Yongsung Chang, David Cook, Chris Edmond, Nils Gornemann, Pierre-Olivier Gourinchas, Matthias Hoelzlein, Rupal Kamdar, Amir Kermani, Soyoung Kim, Woojin Kim, Dmitri Koustas, Young-hwan Lee, Yang Lu, Emi Nakamura, Tommaso Porzio, Walker Ray, David Romer, Nick Sander, Benjamin Schoefer, Dmitriy Sergeyev, Ludwig Straub, Mauricio Ulate, Pengfei Wang, Michael Weber, Jenny Xu, and seminar participants at Berkeley, City University of HK, HKUST, HKU, Seoul National, Yonsei, and the EGSC at Washington University in St. Louis for helpful comments and suggestions. Support from Hong Kong University of Science and Technology Grant No. R9213 is gratefully acknowledged. All errors are my own.

[T]he various linkages between heterogeneity and aggregate demand are not yet well understood, either empirically or theoretically. – Yellen (2016)

1 Introduction

The Great Recession was a pivotal moment for modern business cycle research. One of the key elements revealed by the recession was that distributional factors could have significant effects on macroeconomic fluctuations. Indeed, a major objective of policymakers has since become understanding the distributional effects of macroeconomic stabilization policies and the propagation of these policies via redistribution. However, this is not the only question that the Great Recession posed. Another important issue is whether inequality and redistribution contribute to variation in aggregate demand. If distributional forces can initiate demand-driven business cycles, appropriate policies should be taken to stabilize the economy. In this regard, it is central to understand how the power of stabilization policies varies with the level of inequality. Although the Great Recession spurred interest in these questions, we still possess a limited understanding of the interplay between business cycles, inequality, and stabilization policies, as underscored by former Fed chair Yellen (2016).

This paper investigates the above questions both empirically and theoretically. Using a novel, quarterly time series of inequality, I empirically study how drivers of business cycles cause variations in inequality at cyclical frequencies. I also explore the other direction from inequality to macroeconomic fluctuations. I document that changes in the cross-sectional dispersion of economic resources can significantly influence aggregate demand. To shed light on the mechanisms through which inequality impacts aggregate demand, I develop a new, tractable theoretical framework. This model highlights the interplay among inequality, marginal propensities to consume (MPCs), and aggregate demand in a parsimonious manner. Finally, I discuss an intriguing policy implication of the model that the power of monetary and fiscal policies increases with the level of inequality. These results illustrate why inequality matters for business cycles and stabilization policies and why policymakers should be aware of the distributional outcomes of their policies, even if their objectives only concern aggregate economic conditions.

The greatest hurdle in the empirical analysis is to find a high-frequency measure of inequality.[1] I resolve this problem by constructing a new quarterly inequality index based

[1] Most existing measures of inequality are annual such as the top income share of Piketty and Saez (2003),

on the Quarterly Census of Employment and Wages (QCEW), a quarterly, publicly available, administrative database. I extract an earnings distribution in each quarter from these microdata and construct a time series of inequality measures.

The QCEW publishes counts of employment and pretax earnings at the U.S. county level by detailed industry classification codes. Although the data are not at the individual level, they are disaggregated enough to capture major dynamics of earnings inequality. The number of observations (e.g., 265,805 in 2001:q1) is enormous given the administrative nature of the data source. Furthermore, inequality series based on the QCEW show similar historical trends to existing series based on individual but annual data.

Using this new, high-quality, quarterly time series of earnings inequality, I study how driving forces of business cycles influence earnings inequality. I report impulse response functions (IRFs) and forecast error variance decompositions (FEVDs) of earnings inequality in relation to shocks to total factor productivity, monetary policy, and fiscal policy. I document that an expansionary productivity shock and a contractionary government spending shock significantly reduce earnings inequality in the medium run. However, for the first two years, the responses are small and statistically insignificant for both shocks. On the other hand, monetary policy shocks have little effect on earnings inequality at all horizons. These facts may provide useful empirical inputs to theoretical heterogeneous agent models (for example, Gornemann, Kuester and Nakajima, 2016; Guerrieri and Lorenzoni, 2017; Kaplan, Moll and Violante, 2018; McKay, Nakamura and Steinsson, 2016; McKay and Reis, 2016).

Next, I turn to the other direction, from inequality to business cycles. While studies of business cycles typically focus on level shocks to aggregates, I propose using innovations in inequality as a measure of "redistribution" shocks. Intuitively, rising inequality or redistribution from the poor to the rich may reduce aggregate demand because MPCs decrease in income and wealth (see Dynan, Skinner and Zeldes, 2004; Johnson, Parker and Souleles, 2006; Parker et al., 2013; Zidar, 2019).

Specifically, I rely on unanticipated innovations in the time series of earnings inequality, which are orthogonal to aggregate shocks and macroeconomic variables. In response to these innovations that summarize redistributive forces shifting earnings from the bottom to the top, real GDP, consumption, investment, price levels, and the federal funds rate

the top wealth share of Saez and Zucman (2016), the log P90/P10 wage ratio of Autor, Katz and Kearney (2008), and the Gini coefficient prepared by the U.S. Census Bureau. However, annual data are not suitable for the time-series analysis in this paper due to small sample sizes and difficulties in identifying high-frequency variations.

decrease in a U-shaped manner. The signs of these IRFs imply that aggregate demand is affected by the redistribution of earnings. Furthermore, the responses are substantial; the FEVD of real GDP due to these innovations is 35 percent at a four-year horizon. In short, redistribution shocks are an important cause of business cycles, similar to standard level shocks to aggregates.

To illustrate the amplification and propagation of redistribution shocks, I develop two dynamic stochastic general equilibrium (DSGE) models. I study a simple model to build the intuition based on the analytical results and a medium-sized model to rationalize the large, U-shaped empirical IRFs for aggregate variables. These models feature hand-to-mouth and intertemporal agents in line with Campbell and Mankiw (1989) and Galí, López-Salido and Vallés (2007). Unlike usual two-agent models, however, I assume that the labor productivity of the hand-to-mouth agent is lower than that of the intertemporal agent. This setup accords with the empirical evidence that MPCs decrease in income and wealth, that the probability of being credit constrained decreases in income (Crook, 2001, 2006), and that there is limited participation in financial markets among households with below-median wealth (Guiso and Sodini, 2013).

I consider a shock that increases the dispersion of idiosyncratic labor productivity, which makes the rich richer and the poor poorer. The main analytical result from the simple two-agent New Keynesian (TANK) model is that this redistribution shock affects the output gap and price inflation in the exact same manner as a discount rate shock does in a representative agent New Keynesian (RANK) model. This new finding clearly illustrates why inequality and redistribution can be a primitive source of aggregate demand shocks in a representative agent framework.

However, this simple TANK model (and its standard extensions) cannot rationalize the empirical IRFs, especially the U-shaped patterns. For the quantitative analysis, therefore, I introduce three novel and realistic components into the model: an endogenous extensive margin between two agents, decreasing relative risk aversion (DRRA) consumption utility, and a small amount of financial income for the credit-constrained agents. The interplay of these features induces new channels through which redistribution shocks affect aggregate demand. Furthermore, these new channels help the model to generate large, U-shaped IRFs that are comparable to the empirical IRFs. Because a consumer in my model can only temporarily be hand-to-mouth or intertemporal due to the extensive margin between two agents, I dub the model "the temporarily hand-to-mouth and intertemporal agent New

Keynesian model," or for short, the "THINK" model.

The THINK model further predicts that inequality affects the power of stabilization policies. Intuitively, in an economy with higher inequality, there may be more people at the bottom of either the income or wealth distribution. Because they lack sufficient buffers to absorb shocks, their MPCs are higher. Then, an interaction effect between having more people and higher MPCs makes aggregate consumption demand more sensitive to economic conditions, including monetary and fiscal policies. This channel is relevant to the U.S. economy because the share of households with negative net wealth has been increasing since 1969 (Wolff, 2017). Consistent with this insight, stabilization policies in the THINK model are more powerful when the level of inequality is higher. Furthermore, my empirical results conform to this theoretical prediction. Using a variety of datasets (state level, aggregate, various sample periods and identified shock series), I find that the U.S. economy responds more strongly to policy shocks when income is distributed more unequally.

Literature. There are several empirical studies on cyclical variations in inequality. Some focus on the effects of inflation on poverty or the redistribution of nominal wealth (Blank and Blinder, 1986; Doepke and Schneider, 2006; Romer and Romer, 1999). Others look at differential exposure of individual consumption, earnings, and income to aggregate fluctuations (Parker and Vissing-Jorgensen, 2009; Guvenen, Ozkan and Song, 2014; Guvenen et al., 2017). Coibion et al. (2017) is related to this paper and studies how inequality responds to monetary policy shocks. I extend previous work to other major structural shocks. Furthermore, I investigate how inequality impacts business cycles and articulate the mechanisms at play using structural models, whereas neither of these questions is covered in Coibion et al. Finally, Coibion et al. use the Consumer Expenditure Survey, while my data source is the QCEW.

My model features both hand-to-mouth and intertemporal agents as in Bilbiie (2008), Campbell and Mankiw (1989), and Galí, López-Salido and Vallés (2007). Although these models usually assume equally productive agents and ignore distributional factors, I introduce earnings inequality with heterogeneous labor productivity. This model provides a new, simple theoretical framework for studying inequality and macroeconomic fluctuations. This parsimonious framework is further consistent with the empirical evidence in the sense that less productive workers have higher MPCs and are more likely to be credit constrained (see Crook, 2001, 2006; Dynan, Skinner and Zeldes, 2004; Johnson, Parker and Souleles, 2006; Parker et al., 2013; Zidar, 2019).

To study economic fluctuations with distributional issues, one can develop heterogeneous agent New Keynesian (HANK) models. These quantitative models can generate a realistic description of cross-sectional distributions of households as an equilibrium outcome (see Kaplan and Violante, 2018, for a review). An alternative approach is to construct models with two (or a finite number of) agents as a middle ground between tractable RANK and rich HANK models (Acharya and Dogra, 2018; Bilbiie, 2019; Challe et al., 2017; Debortoli and Galí, 2017; Ragot, 2018; Ravn and Sterk, 2018). I use the latter approach and emphasize insights based on simple, analytical expressions highlighting HANK mechanisms.

The THINK model features an extensive margin between two agents. Bilbiie (2019) considers an analogous channel with fixed transition probabilities in his analytically tractable HANK model. My paper goes one step further and makes transition probabilities vary endogenously with aggregate fluctuations. Because earnings risk is countercyclical as reported by Guvenen, Ozkan and Song (2014), Ravn and Sterk (2017), and Storesletten, Telmer and Yaron (2004), it is harder for credit-constrained agents to escape their constraints in a recession. Thus, the number of credit-constrained agents increases during economic downturns, constituting a new channel for aggregate consumption dynamics (Mian, Rao and Sufi, 2013).

Auclert and Rognlie (2018) also investigate the effects of redistribution shocks on economic output. They find small aggregate effects in their HANK model, contrary to the predictions of my THINK model and empirical results. However, these two models differ from each other in several respects. For example, Auclert and Rognlie assume CRRA preferences and flexible prices, while I assume DRRA preferences and sticky prices. Furthermore, Auclert and Rognlie do not include an autoregressive term in the monetary policy rule, whereas the policy rate is smooth in my model. When all the differences are combined, the two models generate divergent predictions on the effects of redistribution shocks.

Outline. The remainder of this paper is organized as follows. Section 2 covers the construction of the novel, high-quality, high-frequency measure of earnings inequality. Section 3 examines the responses of earnings inequality to shocks to stabilization policies and total factor productivity. In Section 4, I study the direction from earnings inequality to business cycles and illustrate that an unanticipated positive innovation in earnings inequality substantially decreases aggregate demand in a U-shaped manner. Section 5 rationalizes the large, negative, U-shaped responses of aggregate demand to a redistribution shock in DSGE models. Section 6 discusses the relationship between the power of stabilization policies and the level of inequality. Section 7 concludes the paper.

2 A New Quarterly Measure of Inequality

2.1 Data

The QCEW is a quarterly, publicly available, administrative database. The Bureau of Labor Statistics and the state employment security agencies prepare the data based on reports filed by employers, which are collected for unemployment insurance programs.

The employment series covers all forms of jobs: full time, part time, temporary, and permanent. The wages in the data are pretax earnings, including bonuses, stock options, profit distributions, and some fringe benefits, such as the cash value of meals and lodging.

The main advantages of the QCEW are frequency, coverage, and accuracy. First, the QCEW is quarterly, whereas most of the other data previously used for studying inequality are annual.[2] Moreover, the QCEW covers all counties and industries. Finally, the data are administrative and therefore observed with little measurement error.

However, the data are not perfect. First, the data are not at the individual level. The most granular information available is average earnings and the number of workers in a cell, where a cell is an industry/county/ownership-type combination.[3] Thus, measures in this paper represent between-cell, not within-cell inequality. Moreover, self-employed workers are not included, and some observations are suppressed due to confidentiality. Finally, the data cover only earnings.[4]

Although it is not at the individual level, the QCEW is sufficiently disaggregated. For example, the number of cells in the first quarter of 2001 is 265,805, which far exceeds the number of respondents in a typical survey. Furthermore, the log P90/P10 index from the QCEW is consistent with the same measure based on individual-level but annual data (see Section 2.2). In other words, the measurement errors due to the unobservable within-cell

[2]For example, Guvenen et al. (2015), Guvenen, Ozkan and Song (2014), and Song et al. (2018) use the Master Earnings File of the U.S. Social Security Administration. Piketty and Saez (2003) rely on tax return statistics of the Internal Revenue Service. The Current Population Survey (CPS) is analyzed by Autor, Katz and Kearney (2008). The CPS has two types of earnings data. The first type is collected annually in the March annual demographic survey. The other is based on merged outgoing rotation groups (MORG) available monthly. However, the MORG data are about *usual* weekly earnings and, therefore, are not suitable for identifying high-frequency variation in inequality.

[3]The ownership code differentiates establishments owned privately, by a local government, by a state government, by the federal government, and by an international government.

[4]However, taking capital income into account might not significantly affect the log P90/P10 index (the benchmark measure in this paper) because capital income is extremely concentrated above the top 10th percentile.

inequality seem to be small.[5]

I use several filters to attenuate the potential adverse effects of extreme observations and seasonality. First, observations with unreasonably small earnings are dropped. Following Guvenen et al. (2015), the threshold is what can be earned by working one-quarter of full time at half the legal minimum wage rate. Second, I seasonally adjust the percentiles of the log earnings distribution and deflate the nominal variables using the GDP implicit deflator (see Appendix A for details).[6]

Table 1 shows summary statistics for selected quarters. The upper half of Table 1 displays the number of observations and coverage. The number of cells is very large, greater than two hundred thousand after a few early quarters. The lower half of the table shows the sizes of the cells. For example, there are 66 workers in a median-sized cell in the first quarter of 2014, which corresponds to only 0.00007% of the total number of workers. In other words, the sizes of most of the cells, in which I assume workers earn uniformly divided compensation, are small when we consider the cross-section of earnings.

2.2 Percentiles and the Inequality Index

In the right panel of Figure 1, I plot selected percentiles of the real earnings distributions (annualized) in log scale. The U.S. real earnings distribution has widened for the last few decades because the upper half of the distribution has grown fast. Similarly, the gap between the median and the bottom 10th percentile increased throughout most of the periods considered, with the exception of the late 1990s (see also Figure A2 in Appendix A). Finally, the imprints of historical events such as the dot-com bubble around 2000 and the subprime crisis around 2008 are evident among the top percentiles.

The new quarterly log P90/P10 index, which is my benchmark inequality measure, is shown in the left panel. When it is compared with an annual measure reported by Autor, Katz and Kearney (2008), not only the historical pattern but also the values are similar.[7]

[5]Relatedly, Song et al. (2018) argue that changes in earnings inequality in the U.S. have been primarily a between-firm, not within-firm, phenomenon. This might explain why ignoring within-cell inequality leads to little distortion in time-series variation.

[6]All standard macroeconomic variables are obtained from the FRED database operated by the Federal Reserve Bank of St. Louis.

[7]I construct three other measures: the cross-sectional standard deviation of log real earnings, Gini coefficients of real earnings, and top 10% earnings shares. Although these series successfully replicate historical patterns, their levels are lower than the corresponding measures based on individual-level but annual data (Figures A3 and A4 in Appendix A).

Because Autor, Katz and Kearney use individual-level data in the CPS March survey, this similarity indicates that my quarterly series is of high quality.

My new quarterly series has desirable properties for the following reasons. First, the QCEW is a large administrative dataset. Second, although within-cell inequality is not observable, the size of most cells is small. Furthermore, the P90/P10 index is rather robust to changes in within-cell inequality because the index utilizes only two points in the entire distribution. Finally, considering the log P90/P10 index makes it possible to circumvent measuring inequality within the extreme tails and to focus on inequality in the "middle class," who substantially affect aggregate variables.

3 From Aggregate Shocks to Earnings Inequality

This section investigates how earnings inequality reacts to major drivers of business cycles. The estimated IRFs and the FEVDs constitute novel empirical facts regarding the dynamics of earnings inequality.

3.1 Shocks and the Sample Period

I analyze the relationship between my inequality index and structural shocks to total factor productivity (TFP), monetary policy (MP), and fiscal policy (FP). For the TFP shocks, I employ utilization-adjusted changes in productivity, constructed by Fernald (2014) in a similar manner to how Basu, Fernald and Kimball (2006) adjust annual measures. For the MP shocks, Romer and Romer (2004) draw orthogonal components in the federal funds rate to the Federal Reserve's information set. I use an updated version of the series, extended to 2008 by Coibion et al. (2017). Finally, I rely on the FP shock series in Auerbach and Gorodnichenko (2012), which is obtained by comparing the realized growth rates of government spending with its forecasts from the Greenbook and the Survey of Professional Forecasts.

My sample begins in 1978, when major changes to the coverage of the QCEW became effective.[8] The sample ends in 2008, when the updated MP shock series stops.

[8]Specifically, the Federal Unemployment Compensation Amendments of 1976 became effective on January 1, 1978. These amendments incorporated major changes to the state unemployment insurance program on which the raw data of the QCEW are based. See https://www.bls.gov/cew/cewbultncur.htm#Coverage.

3.2 Impulse Responses

Let y_t, $x_{t,1}$, $x_{t,2}$, and $x_{t,3}$ be the inequality index, TFP, MP, and FP shocks in period t, respectively. The response of y_{t+h} to a unit impulse in $x_{t,j}$ is denoted by $\psi_{h,j}$. The IRF, $\{\psi_{h,j}\}$, is estimated using local projections of Jordà (2005):

$$y_{t+h} - y_{t-1} = c_h + \sum_{i=1}^{L_y} \rho_i^{(h)} \Delta y_{t-i} + \sum_{i=0}^{L_x} \sum_{j=1}^{3} \beta_{i,j}^{(h)} x_{t-i,j} + u_{t,h}^{(y)}, \tag{1}$$

where $\beta_{0,j}^{(h)}$ captures $\psi_{h,j}$ for each h and j. In other words, $\{\beta_{0,j}^{(h)} : \ h = 0, 1, \dots\}$ represents how the inequality index responds to $x_{t,j}$. I similarly estimate how the aggregate earnings in the QCEW react to $x_{t,j}$.

In Equation (1), lags of Δy_t and $x_{t,j}$ are included on the right-hand side to absorb the predictable variation. I set L_y and L_x at six, but the results are robust to different choices of lag length and various specification details. Finally, the identified shocks in Equation (1),$x_{t,j}$, are orthogonal to each other. For every pair of the three shocks, the null of zero correlation is not rejected at the 5% level. Details of these statistical tests and sensitivity analysis are in Appendix B.1-3.

The results are depicted in Figure 2. In response to a one-standard-deviation positive TFP shock (3 percent, annualized), the aggregate earnings increase with a peak of approximately 3 percent (annualized) after 10 quarters, and the inequality index decreases by approximately 2.5 log points (annualized) after 3 to 4 years. Thus, the earnings distribution shifts to the right, while the dispersion among the middle 80% shrinks.[9] This result is consistent with the prediction of a heterogeneous agent model in Gornemann, Kuester and Nakajima (2016). Note further that my results pertain to cyclical variation in productivity and inequality around trends, not the trends themselves. Secular patterns in skill-biased technological change and inequality, documented by, e.g., Goldin and Katz (2009) and Krusell et al. (2000), are absorbed by the intercept in Equation (1) and do not appear in $\psi_{h,j}$.

MP shocks have little effect on the earnings dispersion among the employed. Although contractionary MP shocks significantly decrease aggregate earnings, the log(P90/P10) index

[9] The reduction in the inequality index, log(P90/P10), arises mostly because the upper half of the distribution, represented by log(P90/P50), is compressed (Appendix B.5). However, the right tail above P90 reacts differently. Indeed, the P99/P50 index and top 10% share increase given positive TFP shocks (Appendix B.6 and Figure B.7). As a result, the earnings distribution becomes more right-skewed in response to a positive TFP shock.

does not react substantially, which is also consistent with what Coibion et al. (2017) find using a different dataset (see their Figure 3). In theory, contractionary MP shocks may increase or decrease earnings inequality, as is the case in Gornemann, Kuester and Nakajima (2016) and Dolado, Motyovszki and Pappa (2018), respectively. However, in any case, my results imply that the redistribution of earnings should be quantitatively minimal, and the level effects of monetary policy across different earnings groups are fairly uniform. Furthermore, the redistribution channel of monetary policy might be more effective through either unemployment risk, financial income, or the impacts of inflation on nominal wealth, rather than through labor earnings among the employed (see Auclert, 2019; Kaplan, Moll and Violante, 2018, for the redistribution channel).

The earnings distribution widens when government expenditures increase, consistent with the outcome of the model in Heer and Scharrer (2016). The responses in Figure 2 are delayed and persistent like those to TFP shocks. The peak effects are 3.8 log points (annualized) after 15 quarters given a one-standard-deviation shock (4.2 percent, annualized).[10]

3.3 Forecast Error Variance Decompositions

Next, I evaluate the economic significance of each shock as a driver of earnings inequality at business cycle frequencies. I calculate the FEVDs of the inequality index in relation to each shock. The parameters of interest are

$$s_{h,j} = \frac{Var\left(\sum_{i=0}^{h} \psi_{i,j} x_{t+h-i,j}\right)}{Var\left(y_{t+h} - y_{t-1} - P_{t-1}\left(y_{t+h} - y_{t-1}\right)\right)}, \tag{2}$$

where the subscript j indexes the type of shocks (TFP, MP, or FP) and $P_t(\cdot)$ indicates a projection on a period-t information set. The forecast error, $y_{t+h} - y_{t-1} - P_{t-1}(y_{t+h} - y_{t-1})$, consists of the effects of $\{x_{t,j}\}$ and an unrelated component, $u^{(FE)}_{t,h,j}$: $y_{t+h} - y_{t-1} - P_{t-1}(y_{t+h} - y_{t-1}) = \psi_{0,j} x_{t+h,j} + \cdots + \psi_{h,j} x_{t,j} + u^{(FE)}_{t,h,j}$. Then, the contribution of the shock j to the forecast error variance is captured by $s_{h,j}$. In other words, it measures the importance of shock j in explaining the dynamics of y_t at horizon h.

I employ a bias-corrected R^2 estimator of Gorodnichenko and Lee (2019), a flexible method for estimating the FEVDs with local projections. For the projection $P_{t-1}(\cdot)$ in

[10]Similar to the case for the TFP shock, rising dispersion among the upper half is crucial to the reaction. The increase in the P90/P50 index is significantly, whereas that in the P50/P10 index is not (Appendix B.5).

Equation (2), I use the three shocks and Δy_t at lags 1 to 4. I estimate the FEVDs based on the sample both with and without the early Volcker period, during which the Fed targeted the quantity of nonborrowed reserves rather than the federal funds rate. This is because, unlike most of the other results in this paper, the estimated FEVDs for FP shocks are sensitive to several observations between 1979 and 1982.[11] In addition to the sample period, the results are robust to various specification details (Appendix B.4).

The results are shown in the lower half of Figure 2. TFP and FP shocks are major determinants of earnings inequality at the 3- to 4-year horizons. TFP shocks explain approximately 20-30 percent of the forecast error variances of the inequality index. Similarly, approximately 20 percent is due to FP shocks after the early Volcker period. Note that the FEVDs for TFP and FP shocks are consistent with the delayed and persistent IRFs. For MP shocks, the estimated FEVDs are statistically insignificant, similar to the impulse responses, shown in the upper half of Figure 2.

In sum, expansionary FP shocks substantially increase earnings inequality in the medium run. On the other hand, earnings inequality does not react to MP shocks, which is contrary to the predictions of several theoretical heterogeneous agent models. This result further implies that monetary actions are more suitable when policymaker's objective is to design stabilization policies that are neutral to the dispersion of earnings. Finally, TFP shocks have statistically and economically significant medium-run effects on earnings inequality.

Although macroeconomic factors matter for earnings inequality at the 3- to 4-year horizons, they have little effect on earnings inequality at shorter horizons. Similarly, a considerable fraction of the short-run movements of earnings inequality are unpredictable even when the information set is substantially extended. The role of this unanticipated variation in earnings inequality will be studied in the next section as a potential source of business cycles.

4 From Earnings Inequality to Business Cycles

The previous section highlights that drivers of business cycles (especially shocks to TFP and fiscal policy) affect earnings inequality. Here, I focus on the other direction, from earnings inequality to business cycles. I show that inequality itself can substantially impact

[11] Relatedly, Coibion (2012) and Romer and Romer (2004) find that the estimated effects of MP shocks on output are also sensitive to the inclusion of this period in the sample.

aggregate demand by redistributing economic resources across agents with different MPCs, and so policies are called for to stabilize business cycles.

This section begins with heuristics for how shocks to earnings inequality can be related to aggregate demand shocks. In the empirical analyses, I rely on unanticipated innovations in the inequality index, which summarize shocks to individual heterogeneity and redistributive factors in the economy in a parsimonious manner. In response to an unanticipated innovation in inequality that represents redistribution of earnings from the bottom to the top, aggregate variables such as real GDP, the price level, and interest rates decline substantially in a U-shaped manner. The signs of the estimated IRFs imply that redistribution shocks reduce aggregate demand. The FEVDs further highlight that these redistributive forces may be an important source of macroeconomic fluctuations.

4.1 Inequality, Redistribution, and Aggregate Demand

Shocks to inequality can generate aggregate fluctuations. Intuitively, a mean-preserving spread of earnings reduces aggregate consumption demand given a concave consumption function, as shown by Rothschild and Stiglitz (1970, 1971). Furthermore, empirical evidence strongly supports the concavity of the consumption function (Dynan, Skinner and Zeldes, 2004; Johnson, Parker and Souleles, 2006; Parker et al., 2013; Zidar, 2019). Therefore, a redistribution shock constitutes a negative demand shock in a system of aggregate variables. Note that two factors are essential for this heuristic. First, the shocks to inequality reflect redistribution from the bottom to the top. Second, MPCs decrease in income.

4.2 Unanticipated Innovations in Inequality

To empirically evaluate the mechanism above, I begin by identifying redistribution shocks from time-series variation. Specifically, I use an unanticipated innovation, $x_{t,ineq}$, in the inequality index, y_t:

$$y_t - y_{t-1} = \Gamma_x' \mathbf{Z}_t^{(x)} + x_{t,ineq}. \tag{3}$$

The unanticipated innovation in earnings inequality, or in short, a redistribution shock, is a component of y_t orthogonal to the information set, denoted by $\mathbf{Z}_t^{(x)}$. Major macroeconomic variables are included in $\mathbf{Z}_t^{(x)}$, such as the effective federal funds rate (EFFR), inflation, the growth rates of real GDP, consumption, and investment, and the structural shocks to TFP, MP, and FP in Section 3. Throughout this paper, real GDP, consumption, and investment are measured in per capita terms. $\mathbf{Z}_t^{(x)}$ also contains an intercept and 6 lags of Δy_t and the variables above. I include a sufficient number of lags to remove predictable variation as much as possible.

Except for Δy_t, all the contemporaneous variables are included in $\mathbf{Z}_t^{(x)}$. Thus, the identification of $x_{t,ineq}$ is equivalent to that of a structural vector autoregression model with Cholesky ordering where Δy_t is the last variable. By purging all contemporaneous comovements, I define $x_{t,ineq}$ in a conservative manner.

Omitted variable bias might threaten my identification. If there is a demand shock not originating from but affecting earnings inequality, this may distort my empirical results. In this regard, I add three probable confounding factors to $\mathbf{Z}_t^{(x)}$: shocks to an excess bond premium (EBP), news, and consumer confidence. For the EBP, I use average corporate bond premiums unrelated to the systematic default risk of individual firms, following Gilchrist and Zakrajšek (2012). For news shocks, I rely on stock prices, $\ln S_t$, and TFP_t, similar to Beaudry and Portier (2006). The idea is that a component of $\Delta \ln S_t$ unrelated to ΔTFP_t reflects news about the future. Finally, I employ a measure of consumer confidence, E5Y, in Barsky and Sims (2012). Barsky and Sims show that the E5Y contains information on animal spirits in the sense of Lorenzoni (2009).

Although an uncertainty shock may be another confounding factor, it is unlikely to quantitatively affect my estimates. The identified $x_{t,ineq}$ based on the $\mathbf{Z}_t^{(x)}$ above is almost orthogonal to uncertainty shocks in Jurado, Ludvigson and Ng (2015).

Figure 3 depicts the identified redistribution shocks. It follows a white noise process in the sense that the autocorrelations and partial autocorrelations at every lag are statistically insignificant. Furthermore, the redistribution shock does not Granger cause the shocks to TFP, MP, FP, and uncertainty, and vice versa. Finally, the identified shock series is not sensitive to excluding the early Volcker period from the sample (see Appendix C.1).

While it is difficult to rationalize the realized shocks, some of them have narratives related to the distribution of tax changes. The identified series is consistent with leading tax reforms, where the shading in Figure 3 denotes when they were signed into law. For example, the Tax Reform Act of 1986, or Reagan II in Figure 3, reduced the top marginal income tax rates from 50% to 28%. Piketty and Saez (2003) note that, at least temporarily, the earnings distribution widened as a result. It was signed into law in the middle of the fourth quarter of 1986, and $x_{t,ineq}$ was positive in the following quarters. In a similar vein, the

Economic Recovery Tax Act of 1981, or Reagan I, lowered the top tax rate from 70% to 50%, and positive unanticipated innovations followed. Another example is the Omnibus Budget Reconciliation Act of 1993 during the Clinton administration. It raised the top income tax rate from 31% to 39.6%, and the negative $x_{t,ineq}$s in 1993:q4 and the following quarter may be related to the reform. Finally, the Jobs and Growth Tax Relief Reconciliation Act of 2003, or the Bush tax cut, lowered the top rate from 38.6% to 35%. The positive unanticipated innovations in the third and fourth quarters of 2003 might reflect this change.

4.3 Impulse Responses

At the beginning of this section, I proposed the hypothesis that inequality might reduce aggregate demand by redistributing resources from the bottom to the top. Here, I empirically evaluate this hypothesis by looking at how key macroeconomic variables respond to unanticipated innovations in earnings inequality. My results are consistent with the hypothesis in the sense that real GDP, price levels, and interest rates decline simultaneously in response to $x_{t,ineq}$.

I use the following local projections to estimate the IRFs:

$$m_{t+h} - m_{t-1} = \psi_h^{(m)} x_{t,ineq} + \Gamma_m' \mathbf{Z}_t^{(m)} + u_{t,h}^{(m)}, \tag{4}$$

where $\psi_h^{(m)}$ is the parameter of interest, and $\{\psi_h^{(m)} : \ h = 0, 1, \ldots\}$ represents how m responds to a unit redistribution shock. $\mathbf{Z}_t^{(m)}$ includes macroeconomic variables such as EFFR, the GDP deflator inflation rate, and growth rates of real GDP, consumption, and investment, their lags, lags of $x_{t,ineq}$, and an intercept. The lag length is 6, and the results are robust to the lag specification. When estimating the responses of the inequality index, y_t, to the redistribution shock, $x_{t,ineq}$, lags of Δy_t are further added to $\mathbf{Z}_t^{(m)}$.

The results in Figure 4 are consistent with the hypothesis that redistribution shocks affect aggregate demand. A one-standard-deviation unanticipated innovation that increases earnings inequality lowers real GDP by 1.64 percent (annualized) after two years.[12] Similarly, real consumption, investment, and the EFFR decrease. Although negative responses of the GDP deflator after 3 to 4 years are weak, these estimates are sensitive to observations during the early Volcker period. When I use the sample from 1983, the estimated peak effect becomes

[12] Although $x_{t,ineq}$ is a generated regressor, we do not need to adjust the inference when the null hypothesis is that $\psi_h^{(m)} = 0$. See Coibion and Gorodnichenko (2012, Appendix D) and Pagan (1984).

-0.84 percent (annualized) and significant (see Figure C.5). The comovement whereby real GDP, consumption, investment, price levels, and the policy rate decrease simultaneously implies that redistribution shocks reduce aggregate demand. Finally, these variables react in a U-shaped manner, where the peak effects occur after approximately 2 years.

The responses are economically and statistically significant. The magnitudes of the responses are comparable to other prominent structural shocks. For example, one-standard-deviation shocks to MP and TFP affect real GDP by approximately 2 percent (annualized) at the peak (Figures D.2 and D.3), where the peak effect associated with $x_{t,ineq}$ is 1.64 percent. In other words, inequality significantly matters for aggregate fluctuations through its effects on aggregate demand and slack in an economy. Furthermore, the results are robust to various modifications to the baseline specification, such as the consideration of different lag length, exclusion of the early Volcker period, inclusion of federal transfer payments in $\mathbf{Z}_t^{(x)}$, and use of inequality measures other than the log P90/P10 index (see Appendix C.2).

Straub (2018) notes that aggregate implications of changing inequality may depend on whether it is based on permanent or transitory income. Because consumption may be approximately linear in permanent income, growth in permanent income inequality may have little effect on aggregate demand. In this regard, it is intriguing that my redistribution shocks increase the inequality index only temporarily in Figure 4. A one-standard-deviation redistribution shock increases the log P90/P10 index by approximately 2 log points (annualized) concurrently, and the responses gradually return to zero, similar to an AR(1) process. Thus, my series presumably represents shocks to the dispersion of transitory earnings.

4.4 Forecast Error Variance Decompositions

This subsection examines the economic importance of redistribution shocks as a source of U.S. business cycles. Specifically, I estimate the extent to which the forecast error variances of aggregate variables are attributable to unanticipated innovations in earnings inequality.

Figure 5 depicts the results based on bias-corrected R^2 estimators of Gorodnichenko and Lee (2019). Unanticipated innovations in earnings inequality explain the large variation in the log P90/P10 index in the short run, consistent with the IRF in Figure 4 and with the fact that major structural shocks have little effect on earnings inequality in the short run (Section 3.3). The estimate for real GDP at a four-year horizon is 35 percent, with the lower bound of its 90 percent confidence interval being approximately 20 percent. For real consumption and investment, the estimates are 25 and 20 percent at a four-year horizon, respectively, implying that redistributive forces may be an important source of aggregate fluctuations. On the other hand, the EFFR and GDP deflator are mostly driven by other factors. Finally, these results are not sensitive to the specification details (see Appendix C.3).[13]

In summary, the main conclusion in Section 4 is that redistribution shocks can substantially reduce aggregate demand in a U-shaped manner. This novel empirical finding leads to natural follow-up questions regarding the mechanisms at work. The next section develops DSGE models to investigate the amplification and propagation of redistribution shocks and illustrate how the shape and magnitude of the empirical IRFs can be rationalized.

5 Redistribution Shocks in DSGE Models

This section introduces redistribution shocks into DSGE models. I show that a redistribution shock in a simple TANK model resembles a discount rate shock in a textbook RANK model. This result implies that earnings inequality can be a primitive source of aggregate demand shocks in a representative agent framework. For the quantitative evaluation, I develop the temporarily hand-to-mouth and intertemporal agent New Keynesian (THINK) model. I demonstrate how this model rationalizes the large, negative, U-shaped, empirical IRFs in Section 4.

5.1 Redistribution Shocks in a Simple Two-Agent New Keynesian Model

Suppose that there are two types of households. The first type is a hand-to-mouth agent, and the other type can intertemporally smooth their consumption. Following Debortoli and Galí (2017), I call the hand-to-mouth agents Keynesians and the others Ricardians.

The Keynesians are credit constrained and cannot engage in intertemporal optimization. Thus, their consumption is determined by labor earnings. That is, $P_t C_t^K = Z_t^K W_t N_t^K$, where $P_t = \left(\int_0^1 P_{j,t}{}^{1-\epsilon_P} dj\right)^{1/(1-\epsilon_P)}$ is an aggregate price level, W_t is a nominal wage rate,

[13] Because it is difficult to precisely estimate FEVDs using a finite sample, caution needs to be exercised when interpreting the results. In particular, the redistribution shock, which is a generated variable, might involve measurement error. However, Gorodnichenko and Lee (2019) show that measurement errors induce negative asymptotic biases; therefore, my estimates are conservative and in favor of there being no effect.

$C_t^K = \left(\int_0^1 \left(C_{j,t}^K\right)^{(\epsilon_P-1)/\epsilon_P} dj\right)^{\epsilon_P/(\epsilon_P-1)}$ is a composite consumption bundle, and Z_t^K denotes the labor productivity of the Keynesians. They choose hours of work, N_t^K, to equate a real wage rate and a marginal rate of substitution: $Z_t^K \frac{W_t}{P_t} = \frac{v_N(N_t^K)}{u_C(C_t^K)}$, where the period utility function is $U(C^K, N^K) = u(C^K) - v(N^K)$, and subscripts C and N denote the first derivative with respect to C and N, respectively.

On the other hand, the Ricardians maximize $E_t\left[\sum_{\tau=0}^{\infty} \beta^\tau U(C_{t+\tau}^R, N_{t+\tau}^R)\right]$ subject to flow budget constraints: $P_{t+\tau}C_{t+\tau}^R + \frac{B_{t+\tau}^R}{1+i_{t+\tau}} = B_{t+\tau-1}^R + Z_{t+\tau}^R W_{t+\tau} N_{t+\tau}^R + \theta_D^R D_{t+\tau} - T_{t+\tau}$, where B_t^R is an amount of risk-free nominal bonds, i_t is a nominal interest rate, and C_t^R, N_t^R, and Z_t^R are similar to those variables for the Keynesians. D_t denotes aggregate dividends, and I assume that each Ricardian agent owns θ_D^R share of the firms. $\bar{s}^K$ and $\bar{s}^R$ represent the population shares of Keynesians and Ricardians; therefore, $\theta_D^R = 1/\bar{s}^R$. T_t is the lump-sum tax. A Ricardian's problem leads to the following optimality conditions: $1 = E_t\left[\beta \frac{u_C(C_{t+1}^R)}{u_C(C_t^R)} \frac{1+i_t}{1+\pi_{t+1}^P}\right]$ and $Z_t^R \frac{W_t}{P_t} = \frac{v_N(N_t^R)}{u_C(C_t^R)}$, where π_t^P denotes price inflation.

Usually, in TANK models, Z_t^K and Z_t^R are the same, and earnings inequality is excluded from the analysis. I assume instead that $Z_t^K < Z_t^R$. As Keynesians earn less and consume a larger fraction of increases in earnings than Ricardians, the MPC decreases in earnings in my model, consistent with empirical evidence. The coefficient of relative risk aversion (RRA) and the inverse Frisch elasticity of labor supply at the steady state are denoted by γ and φ, respectively.

Firms pay price adjustment costs a la Rotemberg (1982), where the quadratic costs are proportional to ψ_P. I further assume that the central bank uses a standard policy rule to choose i_t. For further details, see Appendix D.1.

In this model, there are two types of distributional factors: the distribution at the steady state and redistribution shocks. First, I denote the consumption and labor shares of the Keynesians at the steady state by $\bar{s}_C^K = \frac{\bar{s}^K \bar{C}^K}{\bar{C}}$ and $\bar{s}_N^K = \frac{\bar{s}^K \bar{Z}^K \bar{N}^K}{\bar{N}}$, where C and N are aggregate consumption and labor in efficiency units, and a bar denotes the value at the steady state. $\bar{s}_C^R$ and $\bar{s}_N^R$ are defined accordingly. Second, the redistribution shock is an exogenous force that decreases Z_t^K and increases Z_t^R such that $\bar{s}_N^K \check{Z}_t^K + \bar{s}_N^R \check{Z}_t^R = 0$ for all t. Here, a check denotes the log-deviation from the steady-state value. This shock induces a mean-preserving spread of the earnings distribution given the steady-state labor hours.

Let x_t be an output gap, $\check{Y}_t - \check{Y}_t^n$, where Y_t^n is the level of output when prices are fully flexible. I further define ϕ_C as $\bar{C}/\bar{Y}$ and ϕ_G as $\bar{G}/\bar{Y}$, where G represents government expenditure. The first-order dynamics of this model can be described by the policy rule for the central bank and the following two equations:

$$x_t = E_t\left[x_{t+1}\right] - \frac{1}{\tilde{\gamma}}\left(i_t - E_t\left[\pi^P_{t+1}\right] - r^n_t\right), \tag{5}$$

$$\pi^P_t = \beta E_t\left[\pi^P_{t+1}\right] + \tilde{\lambda} x_t, \tag{6}$$

where r^n_t is the real interest rate under flexible prices, $\tilde{\lambda} = \frac{\epsilon_P - 1}{\psi_P}\Delta$, $\tilde{\gamma} = \gamma\left(1 - \bar{s}^K_C \phi_C \frac{1+\varphi}{\gamma+\varphi}\Delta\right) / \left(\bar{s}^R_C \phi_C\right)$, and $\Delta = \left(\varphi + \frac{\bar{s}^R_N \gamma}{\bar{s}^R_C \phi_C}\right) / \left[1 - \left(\bar{s}^K_N - \frac{\bar{s}^R_N}{\bar{s}^R_C}\bar{s}^K_C\right)\frac{\gamma(1+\varphi)}{\gamma+\varphi}\right]$. The derivations are in Appendix D.1.2. Note that these equations are observationally equivalent to the dynamic IS curve and the Phillips curve in a standard three-equation RANK model (Galí, 2015; Woodford, 2003).

Inequality matters in this model in two respects. First, the distributional parameters, $\bar{s}^K_C$, $\bar{s}^K_N$, $\bar{s}^R_C$, and $\bar{s}^R_N$, affect the propagation of shocks by changing the slopes, $\frac{1}{\tilde{\gamma}}$ and $\tilde{\lambda}$, in Equations (5) and (6). Second, the redistribution shock impacts $\check{Y}^n_t$ and r^n_t. Here, I focus on the redistribution shocks and relegate details of the first respect to Appendix D.1.1 (see also Bilbiie, 2008). I will further revisit the relationship between the level of inequality and propagation of structural shocks including stabilization policy measures in Section 6.

Suppose that $\check{Z}^K_t$ follows an AR(1) process,

$$\check{Z}^K_t = \rho_Z \check{Z}^K_{t-1} - \sigma_Z u^Z_t, \qquad \text{where } 0 < \rho_Z < 1. \tag{7}$$

The mean-preserving spread assumption, $\bar{s}^K_N \check{Z}^K_t + \bar{s}^R_N \check{Z}^R_t = 0$, implies that $\check{Z}^R_t = \rho_Z \check{Z}^R_{t-1} + \sigma_Z \frac{\bar{s}^K_N}{\bar{s}^R_N} u^Z_t$. To simplify exposition, I further assume that the consumption and labor shares of the Keynesians are the same, $\bar{s}^K_C = \bar{s}^K_N$.[14] In this case, one can show that $\check{Y}^n_t$ becomes unrelated to the redistribution shocks.[15] Furthermore, u^Z_t propagates through the natural rate of interest, r^n_t, in the following manner.

$$\frac{\partial E_t[r^n_{t+\tau}]}{\partial u^Z_t} = -\rho^\tau_Z \frac{\bar{s}^K_C}{\bar{s}^R_C}\frac{1+\varphi}{\gamma+\varphi}\gamma(1-\rho_Z)\sigma_Z \qquad < \qquad 0. \tag{8}$$

The u^Z_t shock that increases earnings inequality decreases r^n_t. Note that this propagation resembles how a contractionary discount rate shock in a RANK model works: when utility

[14] A sufficient condition for $\bar{s}^K_C = \bar{s}^K_N$ is $\phi_G = \frac{\bar{G}}{\bar{Y}} = \frac{1}{\epsilon_P}$. When the steady-state price markup is 20 percent (Rotemberg and Woodford, 1997), this corresponds to ϕ_G being equal to 17 percent.

[15] When $\bar{s}^K_C \neq \bar{s}^K_N$, the redistribution shock has a supply-side effect of altering $\check{Y}^n_t$. However, this effect is small as long as $\bar{s}^K_C$ is close to $\bar{s}^K_N$. See Appendix D.1.2 for an analysis of this general case.

in the future is discounted less, r_t^n decreases, and a representative agent consumes less, as the future becomes more important. Thus, the redistribution shock in the simple TANK model is isomorphic to a demand shock in a RANK model. This result further illustrates why individual heterogeneity can be a source of aggregate demand shocks in a representative agent framework.

Intuitively, $\check{C}_t^K$ is similar to $\check{Z}_t^K$ because the Keynesians are hand-to-mouth. On the other hand, the Ricardians intertemporally smooth their consumption; therefore, $\check{C}_t^R$ is less volatile than $\check{Z}_t^R$. When a large decrease in $\check{C}_t^K$ and a small increase in $\check{C}_t^R$ are combined, aggregate consumption, $\check{C}_t$, negatively responds to u_t^Z. In short, the redistribution shock that increases earnings inequality is a negative aggregate demand shock.

In the model above, $\check{C}_t$ decreases contemporaneously and returns monotonically to zero. Therefore, although the simple TANK model is useful to build intuition, it cannot quantitatively rationalize the U-shaped empirical responses of aggregate consumption in Section 4. While introducing habit formation in preferences for consumption is useful to induce hump-shaped dynamics in response to MP shocks (Woodford, 2003), this is not the case for redistribution shocks. Because the Keynesians consume all of their labor earnings every period, habit formation does not play a central role and $\check{C}_t^K$ closely follows $\check{Z}_t^K$. While the dynamics of $\check{C}_t^R$ are affected by consumption habits, it responds positively to an increase in $\check{Z}_t^R$. By combining the negative AR(1)-like dynamics of $\check{C}_t^K$ and positive hump-shaped responses of $\check{C}_t^R$, the model cannot generate U-shaped responses of $\check{C}_t$ to u_t^Z. To rationalize the empirical IRFs and better understand the propagation of the redistribution shocks, further enhancement of the model is required.

5.2 The THINK Model and Its Quantitative Evaluation

In the previous subsection, I demonstrate analytically that the redistribution shock reduces aggregate consumption demand. Here, I quantitatively examine the effects of the redistribution shock using a two-agent, medium-sized DSGE model building on Christiano, Eichenbaum and Evans (2005) and Smets and Wouters (2007). The model features temporarily hand-to-mouth, intertemporal (THI) agents and New Keynesian (NK) characteristics. This THINK model successfully generates large, U-shaped IRFs comparable to the empirical estimates.

5.2.1 The THINK Model

The THINK model extends the simple TANK model in several respects. Regarding individual heterogeneity, three new features are introduced: an endogenous extensive margin between the Keynesian and Ricardian "families," a DRRA consumption utility, and a small amount of financial income accruing to the Keynesians. Standard frictions in medium-sized NK models are further incorporated, such as investment and capital utilization adjustment costs, sticky wages, and habit formation in preferences.

5.2.1.1 The Keynesian and Ricardian Families

I introduce an extensive margin of being a credit-constrained or unconstrained agent in the model, which makes the population shares of both families endogenously determined. Suppose that s_t^K and s_t^R are the number of members in each family in period t. The transition probability of becoming a Keynesian in period t among agents who were Ricardians in period $t-1$ is denoted by q_t^{RK}, and the other transition probabilities are denoted accordingly. The Keynesian family in period t consists of agents who were Keynesians in period $t-1$ and Ricardians in period $t-1$:

$$s_t^K = s_{t-1}^K q_t^{KK} + s_{t-1}^R q_t^{RK}. \tag{9}$$

It is clear that $q_t^{KR} = 1 - q_t^{KK}$, $q_t^{RR} = 1 - q_t^{RK}$, and $s_t^R = 1 - s_t^K$.

I assume that the probability of remaining in the Keynesian family for an agent who was a Keynesian in the previous period is as follows:

$$q_t^{KK} = \bar{q}^{KK} \left(\frac{Y_t}{\bar{Y}}\right)^{-\eta_Y} \left(\frac{s_{t-1}^K}{\bar{s}^K}\right)^{-\eta_s}, \qquad \eta_Y \geq 0 \quad \text{and} \quad \eta_s \in \mathbb{R}. \tag{10}$$

For special cases, the type of agent is fixed when $\bar{q}^{KK} = 1$, $\eta_Y = 0$, $\eta_s = 0$, and $q_t^{RR} = 1$. If $\bar{q}^{KK} = \bar{s}^K$, $\eta_Y = 0$, $\eta_s = 0$, and $q_t^{RR} = \bar{s}^R$, agents are credit constrained in an identically and independently distributed manner. The parameter η_Y governs the cyclicality of q_t^{KK}. As documented by Guvenen, Ozkan and Song (2014), Ravn and Sterk (2017), and Storesletten, Telmer and Yaron (2004), unemployment risk and idiosyncratic earnings risk are countercyclical. During recessions, more people receive large negative idiosyncratic shocks and become credit constrained. A positive η_Y captures this channel, as q_t^{KK} increases when output Y_t is low. That is, it is difficult to escape from a credit-constrained state during economic downturns. On the other hand, η_s influences the persistence of the number of credit-constrained agents. For example, when $s_{t-1}^K > \bar{s}^K$, a positive η_s lowers the probability of staying in the Keynesian family, which increases the degree of mean reversion in the number of credit-constrained agents, s_t^K.

The parameter η_Y can be microfounded as follows. Suppose that the earnings of agents who were credit constrained in the previous period are represented by an inverse Pareto distribution $\upsilon_{i,t}^{-1} Y_t$, where $\upsilon_{i,t} \sim \text{Pareto}(\eta_Y)$ for $\upsilon_{i,t} \geq \upsilon_m$. I assume further that one needs to earn more than a threshold to circumvent the credit constraint, where the threshold is an aggregate variable. In this setup, q_t^{KK} becomes proportional to $Y_t^{-\eta_Y}$. Intuitively, an increase in aggregate income positively affects individual earnings, which leads to fewer credit-constrained agents. That is, "a rising tide lifts all boats." Furthermore, η_s can be related to the (negative) elasticity of the threshold earnings to the number of credit-constrained agents. For example, consider a case in which $s_t^K > \bar{s}^K$. The additional credit-constrained agents would have enough resources not to be constrained at the steady state; therefore, they are likely to be wealthier on average than those who would be credit constrained at the steady state. Because these additional credit-constrained agents can sell illiquid assets for cash or pledgeable collateral, relatively lower earnings may be sufficient for these agents to escape credit constraints. While such actions are not explicitly modeled here, a positive η_s reflects this channel by lowering the threshold earnings and making more agents circumvent credit constraints. On the other hand, banks may become reluctant to issue new loans to households when many households are already indebted. Banks may have to expend additional efforts on screening because some of the potential borrowers may have poor credit conditions. Therefore, these agents may need more earnings to not be credit constrained. If this channel is important, η_s may be negative. In short, the sign of η_s is not clear a priori, and I let the estimation later pin down a value. See Appendix D.2.3 for more on this microfoundation.

Although one can impose a similar structure on q_t^{RK}, a time-varying q_t^{RK} has little effect on aggregate dynamics around the steady state in the benchmark calibration.[16] Therefore, I shut down this channel and assume that $q_t^{RK} = \bar{q}^{RK}$ and $q_t^{RR} = \bar{q}^{RR}$ to make the model parsimonious and keep my analysis focused.

I assume that each Keynesian receives a positive share, denoted by θ_D^K, of dividends

[16] For example, Equation (9) implies that $\check{s}_t^K = \bar{q}^{KK}(\check{s}_{t-1}^K + \check{q}_t^{KK}) + \bar{q}^{KR}(\check{s}_{t-1}^R + \check{q}_t^{RK})$. Because $s_{t-1}^K + s_{t-1}^R = 1$ and $\check{s}_{t-1}^R = -\frac{\bar{s}^K}{\bar{s}^R}\check{s}_{t-1}^K$, the contribution of the time-varying $\check{q}_t^{RK}$ to $\check{s}_t^K$ depends on $\bar{q}^{KR}$. Because $\bar{q}^{KR} = 0.01$ in the benchmark calibration, $\bar{q}^{KR}\check{q}_t^{RK}$ is negligible.

because even wealth-poor households have some financial investments (Guiso and Sodini, 2013). Furthermore, one could regard a part of this income as government transfers to the poor or pensions. Finally, Kaplan and Violante (2014) documents that wealthy consumers can be credit constrained when they invest in illiquid assets. It is natural to suppose that these agents are credit constrained but receive some financial income.

Similarly, each Ricardian holds $\theta^R_{D,t}$ share of the stocks. Because the population shares of two families are time-varying, at least one of θ^K_D and $\theta^R_{D,t}$ should also be time-varying to satisfy $s^K_t\theta^K_D + s^R_t\theta^R_{D,t} = 1$. I fix θ^K_D for simplicity, and let $\theta^R_{D,t}$ be determined by s^K_t and s^R_t. Note that $\theta^R_{D,t} = \frac{1-\theta^K_D}{1-s^K_t} + \theta^K_D$; therefore, $\theta^R_{D,t}$ increases in s^K_t. This result implies that financial assets are concentrated among fewer people (high $\theta^R_{D,t}$) in a recession when more agents are credit constrained (high s^K_t). Indeed, the correlation between the HP filtered top 10% wealth share in Saez and Zucman (2016) and log real GDP per capita is -0.26. Finally, I assume that $\theta^K_D \leq \theta^R_{D,t}$ in all cases I study.

There is a continuum of agents in both families supplying different types of labor in a monopolistically competitive manner. Subject to quadratic wage adjustment costs based on nominal wage inflation, $\pi^W_{l,t}$, a Keynesian agent has the following budget constraint:

$$P_tC^K_{l,t} = Z^K_tW_{l,t}N^K_{l,t} - \frac{\psi_W}{2}\left(\pi^W_{l,t}\right)^2 Z^K_tW_tN^K_t + \theta^K_DD_t. \tag{11}$$

When a Ricardian becomes a Keynesian, one brings θ^K_D share of the stocks, leaving all the other assets to the Ricardian family. On the other hand, when a Keynesian becomes a Ricardian, one carries all the wealth to the new family. This assumption makes each Keynesian receive a constant fraction of the dividend, $\theta^K_DD_t$, although the number of Keynesians is time-varying. A budget constraint for a type-l Ricardian worker is given by

$$P_tC^R_{l,t} + \frac{B^R_{l,t}}{1+i_t} = B^R_{l,t-1} + Z^R_tW_{l,t}N^R_{l,t} - \frac{\psi_W}{2}\left(\pi^W_{l,t}\right)^2 Z^R_tW_tN^R_t + \theta^R_{D,t}D_t - T_t + R_t, \tag{12}$$

where R_t denotes lump-sum redistribution within the Ricardian family to equalize the financial resources available to the new and continuing Ricardians.

The consumption utility, $u\left(C^\iota_{l,t} - b^\iota C^\iota_{t-1}\right)$ for $\iota \in \{K, R\}$, features an external habit, indexed by b^K and b^R. The coefficient of RRA at the steady state is given by $\frac{\gamma^K}{1-b^K}$ and $\frac{\gamma^R}{1-b^R}$. Note that b^R and γ^R do not necessarily equal b^K and γ^K. I instead consider DRRA preferences, consistent with the empirical results in Calvet, Campbell and Sodini (2009, Section IV.C). In my model, having DRRA corresponds to the condition that $\frac{\gamma^K}{1-b^K} \geq \frac{\gamma^R}{1-b^R}$. Agents in the Keynesian family are more relative risk averse and consume less than those in the Ricardian family.

5.2.1.2 The Labor Market, Firms, and the Central Bank

To focus on the new features in the demand block, I minimize deviations from the supply block of the standard medium-sized DSGE models. I briefly describe these parts here and relegate the details to Appendix D.2.

The labor unions determine the wage rate and labor hours for each worker. The quadratic nominal wage adjustment costs in Equations (11) and (12) induce sticky wages and a wage Phillips curve.[17]

Monopolistically competitive firms choose the price of their product, labor input, investment, and capital utilization rate subject to nominal price adjustment costs, investment adjustment costs, and capital utilization costs. Firm j maximizes the discounted dividends, $E_t\left[\sum_{\tau=0}^{\infty} Q^D_{t,t+\tau} D_{j,t+\tau}\right]$, where the stochastic discount factor ($Q^D_{t,t+\tau}$) is based on the marginal consumption utilities ($u^K_{C,t}$ and $u^R_{C,t}$) weighted by the time-varying population share (s^K_t and s^R_t) and the equity shares (θ^K_D and $\theta^R_{D,t}$):

$$Q^D_{t,t+\tau} = \beta^\tau \frac{s^K_{t+\tau}\theta^K_D u^K_{C,t+\tau} + s^R_{t+\tau}\theta^R_{D,t+\tau} u^R_{C,t+\tau}}{s^K_t \theta^K_D u^K_{C,t} + s^R_t \theta^R_{D,t} u^R_{C,t}} \frac{P_t}{P_{t+\tau}}. \tag{13}$$

Finally, a policy rule for the central bank is as follows:

$$i_t = (1-\rho_i)\bar{i} + \rho_i i_{t-1} + (1-\rho_i)(\zeta_\pi \pi^P_t + \zeta_Y \check{Y}_t) + \sigma_i u^i_t. \tag{14}$$

5.2.2 Calibration and Estimation

Here, I discuss parameter values for the THINK model. First, I calibrate some parameters with commonly used values. For estimation, I match the empirical and model IRFs in

[17] One may instead consider a competitive labor market. For a simple exposition, suppose that $\gamma^K = \gamma^R = \gamma$ and $b^K = b^R = 0$. In this case, the individual labor supply schedule becomes $\check{Z}^\iota_t + \check{w}_t = \varphi \check{N}^\iota_t + \gamma \check{C}^\iota_t$ for $\iota \in \{K, R\}$ in log-linearization. For structural shocks not affecting $\check{Z}^R_t$ or $\check{Z}^K_t$ directly, I have $\gamma(\check{C}^R_t - \check{C}^K_t) = -\varphi(\check{N}^R_t - \check{N}^K_t)$. This result implies that consumption inequality, $\log\left(\frac{C^R_t}{C^K_t}\right)$, and earnings inequality, $\log\left(\frac{Z^R_t N^R_t}{Z^K_t N^K_t}\right)$, are negatively correlated, conditioned on shocks other than the redistribution shocks. This prediction contradicts empirical findings in Coibion et al. (2017) that consumption inequality increases in response to a contractionary MP shock, whereas earnings inequality is unresponsive.

a Bayesian framework following Christiano, Trabandt and Walentin (2010). This limited information approach allows me to focus on the shocks of interest while not being specific about the remainder of the data generating process. I calibrate the parameters about which the empirical IRFs are less informative using statistics from microdata. By doing so, I can reduce the number of parameters to be estimated and sharpen the identification of my estimator. Below, I focus on the parameters governing household heterogeneity and distributional factors. A full list of the parameters can be found in Table 2.

I assume that one-fifth of the population is Keynesian in the steady state following Debortoli and Galí (2017). The consumption and earnings share of the Keynesians, $\bar{s}_C^K$ and $\bar{s}_N^K$, are based on those of the bottom quintile households sorted by wealth in the data (Krueger, Mitman and Perri, 2016; Kuhn and Rios-Rull, 2016).[18]

For the transition probability from the Ricardian family to the Keynesian family at the steady state, $\bar{q}^{RK}$, I note that Equations (9) and (10) lead to

$$\check{s}_t^K = (\bar{q}^{KK} - \bar{q}^{KK}\eta_s - \bar{q}^{RK})\check{s}_{t-1}^K - \bar{q}^{KK}\eta_Y \check{Y}_t \tag{15}$$

and that $\bar{q}^{KK} = 1 - \bar{q}^{KR} = 1 - \frac{\bar{s}^R}{\bar{s}^K}\bar{q}^{RK}$. Here, η_s and η_Y govern the persistence and cyclicality of $\check{s}_t^K$, respectively. Because η_s and η_Y appear only in the above equation in the log-linearized system, I fix $\bar{q}^{RK}$ at 0.0025 and estimate η_s and η_Y later. When $\bar{q}^{RK} = 0.0025$, 4.5 percent of the Ricardians transition to the Keynesians in 5 years at the steady-state transition rates. This rate is similar to the transition probability from positive to strictly negative net worth in the Panel Study of Income Dynamics. For example, this transition probability between 1984 and 1989 (1989 and 1994) is 4.4 (4.7) percent in the data.

Using Equation (11), one can write θ_D^K in terms of $\bar{s}^K$, $\bar{s}_C^K$, $\bar{s}_N^K$, and other parameters (see Appendix D.2.2). Given the benchmark parameter values, θ_D^K becomes 0.44. Because $\bar{s}^K = 0.2$, approximately 9 percent of the total financial income accrues to the Keynesians. This small amount of financial income reflects the presence of wealthy hand-to-mouth agents among the Keynesians (Kaplan, Violante and Weidner, 2014) and the fact that even the wealth-poor households have some financial investments (Guiso and Sodini, 2013).

Some parameters are estimated by matching the empirical and model IRFs in a Bayesian framework following Christiano, Trabandt and Walentin (2010). Specifically, I use the

[18] In light of the wealthy hand-to-mouth agents of Kaplan and Violante (2014), I also consider a case with higher $\bar{s}_C^K$ and $\bar{s}_N^K$. The aggregate implication of the model is not substantially changed much based on different parameter estimates (see Appendix D.2.2.4).

responses of real GDP, consumption, investment, the GDP deflator, and EFFR to one-standard-deviation shocks to redistribution, monetary policy, and TFP. A list of the estimated parameters includes the RRA of the Keynesians (γ^K), ratio of the marginal consumption utilities ($\bar{u}_C^K/\bar{u}_C^R$), negative elasticity of q_t^{KK} with respect to Y_t and s_{t-1}^K (η_Y and η_s), and parameters for capital utilization costs, investment adjustment costs, and exogenous shock processes.

As shown in Figure 4, the empirical responses of the above variables to redistribution shocks are nil at impact by construction. Obviously, this minimum delay restriction may have further effects on the empirical IRFs at short lags. Therefore, I use the responses to redistribution shocks at lags 4-12 for parameter estimation.[19] For details of the estimation, see Appendix D.2.2.

The results are summarized in Table 2. The Keynesian consumption habit parameter, b^K, is assumed to be 0 because pre-MCMC numerical optimizations assign 0 to b^K. γ^K is 8.53 in the posterior mode, which is much greater than $\gamma^R = 2$. Therefore, agents become more risk averse and consuming less when credit constrained. In line with this result, Guiso and Sodini (2013) report that the 90th percentile of a cross-section of coefficients of RRA in the U.S. is 16.4. Given that the population share of the Keynesians is 20 percent and the coefficients of RRA decrease in wealth, my estimate seems reasonable.

The estimated ratio of the marginal consumption utilities at the steady state, $\bar{u}_C^K/\bar{u}_C^R$, is 3.83, implying that the Keynesians value marginal consumption more than the Ricardians. Given the estimates of η_Y and η_s, Equation (15) becomes $\check{s}_t^K = 0.46\check{s}_{t-1}^K - 4.34\check{Y}_t$. Thus, the number of Keynesians is countercyclical. When output decreases by 1 percent, s_t^K increases by $4.34 \times \bar{s}^K = 0.87$ percentage points.

Given a one-standard-deviation redistribution shock, the productivity of the Keynesians, Z_t^K, decreases by σ_Z in log-deviation (Equation (7)). To better understand the value of σ_Z, I compute how much the log P90/P10 index, y_t, responds to the same shock. Suppose that there exists a continuum of agents whose idiosyncratic log labor productivity, denoted by $z_{i,t}$, is normally distributed. Let σ_t be its cross-sectional standard deviation. Then, $y_t = \sigma_t[\mathcal{N}^{-1}(0.9) - \mathcal{N}^{-1}(0.1)] = -2\sigma_t\mathcal{N}^{-1}(0.1)$, where $\mathcal{N}^{-1}(\cdot)$ is the inverse cumulative distribution function of the standard normal distribution. Because the population share

[19] For the other shocks, when this restriction is not relevant to the identification, I utilize the contemporaneous responses to inform the short-run dynamics. The responses at lags 1-3 are dropped to avoid overweighting these cases, especially the dynamics due to TFP shocks. However, the results are robust to this choice.

of the Keynesians is 0.2, the 10th percentile of $z_{i,t}$ can be related to $\log(Z_t^K)$. That is, $\log(Z_t^K) \approx \sigma_t \mathcal{N}^{-1}(0.1)$, ignoring the mean that is preserved by redistribution shocks. Finally, it follows that $y_t - \bar{y} \approx -2[\log(Z_t^K) - \log(\bar{Z}^K)] = -2\check{Z}_t^K$. As shown in Figure 4, a one-standard-deviation redistribution shock increases y_t by 2 log points (annualized) or 0.5 log points at a quarterly frequency. This effect translates into a decrease in $\log(Z_t^K)$ by 25 log basis points, which is similar to the posterior mode of σ_Z, 28 log basis points.

Figure 4 illustrates how major macroeconomic variables respond to a one-standard-deviation redistribution shock in the data and the estimated THINK model. The fit of the model is reasonably good in the sense that the peak effects and shapes of the IRFs are similar. The estimated model can also replicate the empirical responses to MP and TFP shocks. For the robustness of the results, see Appendix D.2.2.

In summary, the redistribution shock in the estimated THINK model substantially reduces aggregate demand in a U-shaped manner. This result calls for a further inspection of aggregate demand in this model, which is the topic of the next subsection.

5.2.3 Aggregate Demand in the THINK Model

This subsection studies amplification and propagation of the redistribution shock in the THINK model with a focus on aggregate demand. I investigate the source of the large, U-shaped decline in aggregate demand and how it relates to the new features in this model. Below, I discuss the responses of C_t^K, C_t^R, I_t, and C_t to the redistribution shock that increases earnings inequality.

The Keynesians are hand-to-mouth. When a redistribution shock lowers labor productivity, Z_t^K, their earnings and therefore consumption, C_t^K, decrease. However, this *direct effect* on C_t^K may not be crucial for the U-shaped decline in aggregate demand for three reasons. First, in log-linearization, a 1 percent decrease in C_t^K implies a $\bar{s}_C^K$ percent decrease in aggregate consumption, where $\bar{s}_C^K$ is the consumption share of the Keynesians at the steady state. However, $\bar{s}_C^K$ is small, only 11 percent in the benchmark calibration. Second, $\{Z_t^K\}$ is only moderately persistent. Its half-life is approximately 3 quarters given $\hat{\rho}_Z = 0.78$. Finally, the dividend income, $\theta_D^K D_t$, in Equation (11) is countercyclical, conditioned on the redistribution shock. Therefore, a decline in earnings for the Keynesians is more or less offset by an increase in the dividend, dampening the response of C_t^K.

The Ricardians are aware of the fact that there is a chance of receiving large negative idiosyncratic shocks and being credit constrained in the next period. Therefore, the Euler equation for the Ricardians becomes $1 = E_t\left[\beta \frac{q^{RR}_{t+1} u^R_{C,t+1} + q^{RK}_{t+1} u^K_{C,t+1}}{u^R_{C,t}} \frac{1+i_t}{1+\pi^P_{t+1}}\right]$, where $u^\iota_{C,t} \equiv u'\left(C^\iota_t - b^\iota C^\iota_{t-1}\right)$ for $\iota \in \{K, R\}$. In log-linearization, the Euler equation becomes

$$\check{u}^R_{C,t} = \beta(1+\bar{i})\left(\bar{q}^{RR} E_t\left[\check{u}^R_{C,t+1}\right] + \bar{q}^{RK} \frac{\bar{u}^K_C}{\bar{u}^R_C} E_t\left[\check{u}^K_{C,t+1}\right]\right) + \left(\check{i}_t - E_t\left[\pi^P_{t+1}\right]\right), \tag{16}$$

where $\check{i}_t \equiv \log\left(\frac{1+i_t}{1+\bar{i}}\right)$. Two nonstandard aspects in Equation (16) reflect idiosyncratic risks and precautionary motivation. First, the Ricardians care about not only $\check{u}^R_{C,t+1}$ but also $\check{u}^K_{C,t+1}$ as in Bilbiie (2019) and Challe et al. (2017). Second, $\beta(1+\bar{i}) < 1$, similar to the discounted Euler equation of McKay, Nakamura and Steinsson (2017). This is because $\beta(1+\bar{i}) = \left[1 + \bar{q}^{RK}\left(\frac{\bar{u}^K_C}{\bar{u}^R_C} - 1\right)\right]^{-1}$ and $\bar{u}^K_C > \bar{u}^R_C$.

When a redistribution shock increases the productivity of the Ricardians, their consumption, C^R_t, responds positively in a hump-shaped manner. There are two reasons for the hump-shaped responses. First, $u^R_{C,t}$ features consumption habits. Second, the redistribution shock reduces $E_t\left[\check{C}^K_{t+1}\right]$ or equivalently increases $E_t\left[\check{u}^K_{C,t+1}\right]$. In Equation (16), an increase in $E_t\left[\check{u}^K_{C,t+1}\right]$ has a positive effect on $\check{u}^R_{C,t}$, corresponding to a negative effect on C^R_t. Because being credit constrained is more unpleasant than usual, the Ricardians exercise more precaution and consume less contemporaneously.[20] For these reasons, the initial increase in $\check{C}^R_t$ is rather muted. This muted response of $\check{C}^R_t$ helps the concurrent decline in $\check{C}^K_t$ to propagate and reduce aggregate demand. However, it is clear that this *direct effect* on $\check{C}^R_t$ cannot initiate a recession in response to the redistribution shock because the Ricardians increase their consumption.

The two-agent structure in the THINK model adds a new dynamic to investment through the discount factor that firms use to discount future profits. The discount factor, $Q^D_{t,t+\tau}$, is given by $\beta^\tau \frac{s^K_{t+\tau}\theta^K_D u^K_{C,t+\tau} + s^R_{t+\tau}\theta^R_{D,t+\tau} u^R_{C,t+\tau}}{s^K_t \theta^K_D u^K_{C,t} + s^R_t \theta^R_{D,t} u^R_{C,t}} \frac{P_t}{P_{t+\tau}}$ as in Equation (13). In response to the redistribution shock, $u^K_{C,t}$ increases substantially because C^K_t decreases and γ^K is high. In other words, one more unit of financial income becomes much valuable because the constrained agents have to significantly reduce their consumption. As a result, the utility value of the current marginal profit $s^K_t \theta^K_D u^K_{C,t} + s^R_t \theta^R_{D,t} u^R_{C,t}$ increases and $Q^D_{t,t+\tau}$ decreases.[21] This decrease in $Q^D_{t,t+\tau}$

[20]The DRRA preference further amplifies this effect. Because $\check{u}^K_{C,t+1} = -\gamma^K \check{C}^K_{t+1}$, $\check{u}^R_{C,t} = -\frac{\gamma^R}{1-b^R}(\check{C}^R_t - b^R \check{C}^R_{t-1})$ and $\gamma^K > \frac{\gamma^R}{1-b^R}$, $\check{u}^K_{C,t+1}$ is more sensitive to $\check{C}^K_{t+1}$ than $\check{u}^R_{C,t}$ to $\check{C}^R_t$. Therefore, $\check{C}^R_t$ should decrease more than the decrease in $\beta(1+\bar{i})\bar{q}^{RK}\frac{\bar{u}^K_C}{\bar{u}^R_C} E_t[\check{C}^K_{t+1}]$ to match both sides of Equation (16).

[21]Although the other terms in $Q^D_{t,t+\tau}$ may vary, the marginal utilities are the most quantitatively important

leads to a lower present discounted value of the future dividends and therefore a lower value of physical capital in the present. As the current value of physical capital decreases, firms reduce investments accordingly.

Next, I discuss aggregate consumption, $C_t = s_t^K C_t^K + s_t^R C_t^R$, in detail. In log-linearization, I have the following decomposition of C_t into three pieces:

$$\check{C}_t = \bar{s}_C^K \check{C}_t^K + \bar{s}_C^R \check{C}_t^R + \left(\bar{s}_C^K - \bar{s}_C^R \frac{\bar{s}^K}{\bar{s}^R}\right) \check{s}_t^K. \tag{17}$$

This decomposition of aggregate consumption highlights a key, novel propagation mechanism in the THINK model. The first and second terms represent the *direct effects* on C_t^K and C_t^R. When the redistribution shock reduces $\check{Z}_t^K$, $\check{C}_t^K$ decreases, while the opposite holds for the Ricardians. These direct effects explain the entire variation in $\check{C}_t$ in other TANK models where agents' types are fixed or s_t^K and s_t^R are constant. However, my model features an additional channel due to the time-varying number of credit-constrained agents. In the THINK model, a higher $\check{s}_t^K$ leads to lower aggregate consumption because individuals who become credit constrained substantially reduce their consumption. The last term in Equation (17) represents this *distributional effect*, where the coefficient on $\check{s}_t^K$ is negative.[22] Because $\check{s}_t^K$ is countercyclical, as illustrated in Equation (15), the last term in Equation (17) is procyclical, amplifying aggregate fluctuations.

Figure 6 shows how the three terms in Equation (17) and aggregate consumption respond to a one-standard-deviation redistribution shock. As discussed above, the direct effects on C_t^K contribute little to the responses of aggregate consumption after a few quarters. In addition, the direct effects on C_t^R are positive. Thus, the negative, U-shaped responses of aggregate consumption are mostly driven by distributional effects.

Recall that investment decreases in response to the redistribution shock. A decline in investment, combined with the direct effects on Keynesian consumption, lowers aggregate demand. As the economy enters a recession, idiosyncratic earnings risk increases; therefore, some Ricardians become credit constrained. As they become Keynesians, their consumption decreases, which further reduces aggregate demand. As a result, the recession deepens, idiosyncratic earnings risk further increases, more Ricardians become Keynesians, and the process continues. This aggregate demand spiral amplifies the distributional effects, making

driver of $Q_{t,t+\tau}^D$ (see Appendix D.2.5).

[22]Note that $\frac{\bar{s}_C^K}{\bar{s}^K} = \frac{1}{\bar{s}^K}\left(\frac{\bar{s}^K \bar{C}^K}{\bar{C}}\right) = \frac{\bar{C}^K}{\bar{C}}$. Thus, the condition that $\bar{C}^K < \bar{C}^R$ implies that $\frac{\bar{s}_C^K}{\bar{s}^K} < \frac{\bar{s}_C^R}{\bar{s}^R}$.

it the major source of aggregate consumption fluctuations.[23]

It is clear from Equations (15) and (17) that the value of η_Y is crucial for determining the magnitude of the distributional effects. Here, I provide three facts to supplement the discussion and support my estimate of η_Y (4.38), shown in Table 2.[24] First, in the development of the Great Recession, many people were credit constrained because access to credit was limited (Mian, Rao and Sufi, 2013; Mian and Sufi, 2015). Consistent with this episode, a positive η_Y in my model makes the number of credit-constrained agents countercyclical. Second, unemployment risk may contribute to the countercyclical variations in $\check{s}_t^K$. Given $\eta_Y = 4.38$ and other parameters, Equation (15) becomes $\check{s}_t^K = 0.46\check{s}_{t-1}^K - 4.34\check{Y}_t$. Thus, the semi-elasticity of s_t^K with respect to output is $\frac{\partial s_t^K}{\partial \check{Y}_t} = -4.34 \times \bar{s}^K = -0.87$, meaning that the population share of the Keynesian family increases by 0.87 percentage points when output decreases by 1 percent. A similar semi-elasticity of the unemployment rate with respect to real GDP per capita in the U.S. is -0.44 based on the HP filtered quarterly series. Because there also exists countercyclical earnings risk conditioned on being employed (Guvenen, Ozkan and Song, 2014), the sensitivity of $\check{s}_t^K$ to $\check{Y}_t$ in my model may not be unreasonably large. Finally, I can rely on the microfoundation in Section 5.2.1 to draw insights on η_Y from the data. This microfoundation assumes that the left tail of the earnings distribution can be approximated by an inverse Pareto random variable $\upsilon_{i,t}^{-1} Y_t$, where $\upsilon_{i,t} \sim \text{Pareto}(\eta_Y)$. When I derive this Pareto coefficient from the QCEW data, I obtain similar values to my estimate of η_Y. See Appendix D.2.3 for details.

Thus far, I have shown how redistribution can be a source of demand-driven business cycles. The three novel features, an extensive margin of being credit constrained, DRRA preferences, and a small amount of financial income accruing to the constrained agents, helped the THINK model rationalize the large, negative, U-shaped empirical impulse responses of aggregate variables. In doing so, I relied on methods developed for studying linear systems. However, inequality may have a nonlinear effect of altering how an economy

[23] Auclert and Rognlie (2018) also study a redistribution shock and find that its aggregate effects are small in their HANK model. However, their model features a CRRA preference and flexible prices, and an autoregressive term is not included in the monetary policy rule, unlike my THINK model. When I change parameters to make the THINK model similar to the model in Auclert and Rognlie, the THINK model also predicts little effect of the redistribution shock on real variables. Furthermore, each of the factors above is important for my rationalization of the large, U-shaped estimated responses in Section 4. For example, when I fix ρ_i at 0 while not changing the other parameters, the peak effect of the redistribution shock on output becomes less than half of that in the benchmark case (see Appendix D.2.4).

[24] Because quarterly time-series data on s_t^K are not available, it is difficult to calibrate η_Y directly from Equation (15).

responds to stabilization policies and other structural shocks. Investigating this question requires a separate approach because of its nonlinear nature.

6 Inequality and the Power of Stabilization Policies

This section covers policy implications of rising inequality in the U.S. Intuitively, when the level of inequality is higher, there are more people who are earnings- or wealth-poor and therefore have higher MPCs. Then, an interaction effect between more people and higher MPCs can make aggregate consumption demand sensitive to economic conditions and stabilization policies. Consistent with this intuition, the THINK model predicts that the power of stabilization policies increases in the level of inequality. Empirical evidence based on various datasets is also in line with this prediction. In addition to my findings that inequality and redistributive factors can drive macroeconomic fluctuations, this policy implication provides another reason why understanding inequality is important for policymakers.

6.1 Policy Implications of the THINK Model

To understand the relationship between the power of stabilization policies and the level of inequality, the following decomposition of aggregate consumption in the THINK model is useful. Let ds_t^K be $s_t^K - \bar{s}^K$. Other linear deviations are denoted similarly. From $C_t = s_t^K C_t^K + s_t^R C_t^R$, it follows that

$$dC_t = \bar{s}^K dC_t^K + \bar{s}^R dC_t^R + (\bar{C}^K ds_t^K + \bar{C}^R ds_t^R) + (ds_t^K dC_t^K + ds_t^R dC_t^R). \tag{18}$$

Note that this is an exact equation, not an approximation. When compared with Equation (17), the first three terms in Equation (18) correspond to the direct and distributional effects in the log-linear approximation. However, there exists an additional term, representing the interaction effect between distribution (ds_t^K and ds_t^R) and changes in individual consumption that are tightly related to MPCs (dC_t^K and dC_t^R). Thus, aggregate consumption demand can respond more sensitively to stabilization policies when there are more agents with higher MPCs. If the same mechanism applies to other structural shocks, aggregate fluctuations may become larger, and macroeconomic volatility in general may be elevated. Fortunately, however, stabilization policies also become more powerful.

In the U.S., the number of people at the bottom of wealth distribution, where people have high MPCs, has increased in parallel with the levels of earnings and income inequality. For example, Wolff (2017) reports that the share of households holding nonpositive net worth (less than \$5,000 constant 1995 dollars) increased by approximately 6 (13) percentage points from 1969 to 2013 in the U.S.

In light of these changes, I consider two initial states of the model economy: high and low inequality. In the high (low) inequality state, s^K_{t-1} is 0.25 (0.15), and all the other variables equal their steady-state values. The range of 10 percentage points is around the midpoint between 6 and 13 percentage points in Wolff (2017). Based on a third-order approximation to the THINK model, I compute the generalized IRFs, conditioned on the high- and low-inequality states. Figure 7 shows the generalized IRFs of aggregate consumption, given that s^K_{t-1} is 0.25 or 0.15. The left panel illustrates the generalized IRFs to a one-standard-deviation contractionary MP shock, while the right panel presents the corresponding results for an expansionary FP shock. It is clear from both panels that aggregate consumption responds more strongly to policy shocks when the level of inequality is higher. The results for other variables are similar (Appendix E.1). Thus, stabilization policies in the THINK model become more powerful when the level of inequality is higher.

The discussion thus far illustrates a mechanism through which the level of inequality can affect the propagation of structural shocks. Among many structural shocks, I have concentrated on monetary and fiscal policy shocks and derived novel policy implications. In the next subsection, I empirically test this theoretical prediction.

6.2 The Empirical Evidence

Here, I investigate several datasets to test the novel policy implications above. The main idea is to include an interaction term between an inequality measure and a structural shock in local projections. Consistent with the theoretical prediction, the coefficient on this interaction term is statistically and economically significant, implying that inequality matters for the propagation and amplification of stabilization policies.

I examine three different datasets to enhance the robustness of the results. The first dataset consists of quarterly observations of earnings inequality, various aggregate variables, and several structural shocks in recent decades. The second dataset includes an annual but long history of income inequality, some aggregate variables, and a military news shock. The last dataset is based on state-level annual series of income inequality, real GDP, and military procurement spending since the 1960s. For identification, I exploit time-series variation in the first two datasets and variation across states and time in the last dataset. For all the data, shocks, and specifications, the results consistently imply that more inequality leads to larger responses to policy shocks of the same size, consistent with the theoretical policy implications of my THINK model.

6.2.1 Recent Data

The first dataset consists of quarterly observations including the MP and FP shocks, my log P90/P10 index based on the QCEW, and major macroeconomic variables in Sections 2-4.[25] I consider the following local projections with an interaction term, $x_t y_{t-1}$:

$$m_{t+h} - m_{t-1} = \beta_h x_t + \gamma_h x_t y_{t-1} + \Gamma'_{xy,h} \mathbf{Z}^{(xy)}_{t-1} + u^{(xy)}_{t,h}, \tag{19}$$

where x_t represents a unit structural shock and y_{t-1} is the inequality index in the previous quarter. A macroeconomic variable, m_t, responds to the shock by $\beta_h + \gamma_h y_{t-1}$ after h periods. Therefore, the response of m_t depends on the level of inequality, y_{t-1}, and the dependence is parametrized by γ_h. $\mathbf{Z}^{(xy)}_{t-1}$ includes an intercept and four lags of x_t, y_t, $x_t y_{t-1}$, Δm_t, and $\Delta m_t y_t$. The sample period is from 1978:q1 to 2008:q4.

Panel (a) of Figure 8 shows the estimated response of aggregate consumption to a one-standard-deviation contractionary MP shock, conditioned on y_{t-1} being plus or minus one standard deviation from the average. It is clear that the contractionary effects of the MP shock are much stronger when earnings inequality is higher. Relatedly, the null hypothesis that $\gamma_h = 0$ is rejected at the 10 percent level for all h between 9 and 17. The results are similar for the FP shocks, as illustrated in panel (b). In response to a one-standard-deviation expansionary FP shock, consumption increases more when earnings are more unequally distributed. $\hat{\gamma}_h$ is also statistically significant at the 10 percent level for all h between 7 and 11. Thus, I conclude that high earnings inequality makes contractionary MP shocks more contractionary and expansionary FP shocks more expansionary. Finally, the estimates for other macroeconomic variables are in line with these findings (Appendix E.2).

[25] See Appendix E.2 for the results based on the TFP shocks.

6.2.2 Historical Data

Although the results above are intriguing, one might be concerned about a rising trend in inequality during the sample period. In the worst case, earnings inequality might simply capture a trend in the U.S. economy becoming more volatile for other reasons.

To address this concern, I examine a long history of inequality and economic growth in the U.S. since the early 20th century. The top 10% income share of Piketty and Saez (2003) is suitable for this purpose because it starts in 1917. Important for my identification, it follows a U-shaped pattern instead of an upward trend.

The cost of extending the sample backward is that few reliably identified shock series are available. The narrative measure of military news shocks constructed by Ramey and Zubairy (2018) is an exception, dating back to 1889. By combining the two sources, I obtain data spanning from 1917 to 2015.

I estimate Equation (19) using the historical data, where the dependent variable is real GDP per capita. As illustrated in panel (c) of Figure 8, the U.S. economy responds more strongly to military news shocks when the top 10 percent takes more income. For example, a military news shock with a present-discounted value of 10 percent of trend GDP increases real GDP per capita by 4.9 percent after 3 years when the top 10% income share is 47.1 percent, as in 2010. However, the same shock raises real GDP per capita only by 1.3 percent when the top 10% holds 33.5 percent of income, as in 1980. Similarly, the GDP deflator and unemployment rate react more strongly to the shock, conditioned on higher inequality (Appendix E.3).

6.2.3 State-Level Data

Finally, I compare states with different levels of inequality. For inequality, I employ the Frank-Sommeiller-Price series for the top 10% income share by state (Frank et al., 2015). This series is constructed by applying methods similar to Piketty and Saez (2003) at the state level. For state GDP and military procurement spending, I use the data from Nakamura and Steinsson (2014). The sample period is from 1969 to 2008.

Let $m_{i,t}$, $g_{i,t}$, and $y_{i,t}$ be real GDP per capita, real military procurement spending per capita, and the top 10% income share in state i in year t. m_t and g_t without the subscript i

refer to the same variables at the U.S. level. I estimate the following panel regression:

$$\frac{m_{i,t+h} - m_{i,t-1}}{m_{i,t-1}} = \beta_h \frac{g_{i,t} - g_{i,t-1}}{m_{i,t-1}} + \gamma_h \frac{g_{i,t} - g_{i,t-1}}{m_{i,t-1}} \times y_{i,t-1} + \Gamma'_{i,t,h} \mathbf{Z}_{i,t} + u_{i,t,h}, \tag{20}$$

where m and g are now in levels, not in logarithms. Instrumental variables, $D_i \times \frac{g_t - g_{t-1}}{m_{t-1}}$ for all i, are used for the first two regressors in Equation (20), where D_i is a dummy variable for state i. $\mathbf{Z}_{i,t}$ includes time and state fixed-effects, $\frac{m_{i,t-1} - m_{i,t-2}}{m_{i,t-2}}$, and $y_{i,t-1}$. Standard errors are clustered by state.

When aggregate military expenditures increase, some states receive more military spending or also have higher income inequality. My identifying assumption, similar to that of Nakamura and Steinsson (2014), is that the U.S. does not engage in aggregate military buildups because these states are experiencing or expected to suffer from sluggish growth relative to the others.

The results are shown in panel (d) of Figure 8. Consistent with the other results, fiscal expansion is more powerful in states where income inequality is higher. In response to a military spending shock that amounts to 1 percent of real state GDP ($\frac{g_{i,t} - g_{i,t-1}}{m_{i,t-1}} = 0.01$), real state GDP per capita increases by 12.5 (1.2) percent when the top 10% income share is 47.1 (33.5) percent. Furthermore, $\hat{\gamma}_h$ is positive and statistically significant at the 1 percent level for $h = 1$, 2, and 3.

In summary, I examined the three datasets above and relied on several variations to identify the effects of the level of inequality on the propagation of monetary and fiscal policies. The results from these extensive empirical investigations are consistent with the policy implication of the THINK model that the power of stabilization policies increases in the level of inequality.

7 Conclusion

The Great Recession stimulated interest in how inequality, aggregate fluctuations, and stabilization policies are related. Using a new quarterly measure of earnings inequality based on high-quality administrative data, I illustrate that inequality matters for policymakers in three respects. First, earnings inequality reacts to fiscal policy and total factor productivity shocks at business cycle frequencies. Second, unanticipated increases in earnings inequality induce recessions by reducing aggregate demand in a U-shaped manner. Finally, higher levels of inequality make stabilization policies more powerful.

I further develop a new, tractable theoretical framework that rationalizes my empirical findings. This framework provides novel insights into the mechanisms through which inequality affects aggregate demand and the power of stabilization policies. The simplicity of the approach can help researchers easily link models to data and thus stimulate further research in this area, which has historically relied on computationally intensive heterogeneous agent models.

References

Acharya, Sushant, and Keshav Dogra. 2018. "Understanding HANK: Insights from a PRANK." *Manuscript.*

Andreasen, Martin M., Jesús Fernández-Villaverde, and Juan F. Rubio-Ramírez. 2017. "The pruned state-space system for non-linear DSGE models: Theory and empirical applications." *Review of Economic Studies* 85(1): 1–49.

Auclert, Adrien. 2019. "Monetary policy and the redistribution channel." *American Economic Review* 109(6): 2333–67.

Auclert, Adrien, and Matthew Rognlie. 2018. "Inequality and aggregate demand." National Bureau of Economic Research Working Paper 24280.

Auerbach, Alan J., and Yuriy Gorodnichenko. 2012. "Measuring the output responses to fiscal policy." *American Economic Journal: Economic Policy* 4(2): 1–27.

Autor, David H., Lawrence F. Katz, and Melissa S. Kearney. 2008. "Trends in US wage inequality: Revising the revisionists." *Review of Economics and Statistics* 90(2): 300–323.

Barsky, Robert B., and Eric R. Sims. 2012. "Information, animal spirits, and the meaning of innovations in consumer confidence." *American Economic Review* 102(4): 1343–77.

Basu, Susanto, John G. Fernald, and Miles S. Kimball. 2006. "Are technology improvements contractionary?" *American Economic Review* 96(5): 1418–1448.

Beaudry, Paul, and Franck Portier. 2006. "Stock prices, news, and economic fluctuations." *American Economic Review* 96(4): 1293–1307.

Bilbiie, Florin O. 2008. "Limited asset markets participation, monetary policy and (inverted) aggregate demand logic." *Journal of Economic Theory* 140(1): 162–196.

Bilbiie, Florin O. 2019. "The New Keynesian cross." *Journal of Monetary Economics* forthcoming.

Blank, Rebecca M., and Alan S. Blinder. 1986. "Macroeconomics, income distribution, and poverty." In *Fighting Poverty: What Works and What Does Not.* , ed. Sdon Danziger. Cambridge:Harvard University Press.

Calvet, Laurent E., John Y. Campbell, and Paolo Sodini. 2009. "Fight or flight? Portfolio rebalancing by individual investors." *Quarterly Journal of Economics* 124(1): 301–348.

Campbell, John Y., and N. Gregory Mankiw. 1989. "Consumption, income, and interest rates: Reinterpreting the time series evidence." *NBER Macroeconomics Annual* 4: 185–216.

Challe, Edouard, Julien Matheron, Xavier Ragot, and Juan F. Rubio-Ramirez. 2017. "Precautionary saving and aggregate demand." *Quantitative Economics* 8(2): 435–478.

Chetty, Raj, Adam Guren, Day Manoli, and Andrea Weber. 2011. "Are micro and macro labor supply elasticities consistent? A review of evidence on the intensive and extensive margins." *American Economic Review: Papers & Proceedings* 101(3): 471–75.

Christiano, Lawrence J., Martin Eichenbaum, and Charles L. Evans. 2005. "Nominal rigidities and the dynamic effects of a shock to monetary policy." *Journal of Political Economy* 113(1): 1–45.

Christiano, Lawrence J., Mathias Trabandt, and Karl Walentin. 2010. "DSGE models for monetary policy analysis." In *Handbook of Monetary Economics*. Vol. 3, 285–367. Elsevier.

Coibion, Olivier. 2012. "Are the effects of monetary policy shocks big or small?" *American Economic Journal: Macroeconomics* 4(2): 1–32.

Coibion, Olivier, and Yuriy Gorodnichenko. 2012. "What can survey forecasts tell us about information rigidities?" *Journal of Political Economy* 120(1): 116–159.

Coibion, Olivier, Yuriy Gorodnichenko, Lorenz Kueng, and John Silvia. 2017. "Innocent Bystanders? Monetary policy and inequality." *Journal of Monetary Economics* 88: 70–89.

Crook, Jonathan. 2001. "The demand for household debt in the USA: evidence from the 1995 Survey of Consumer Finance." *Applied Financial Economics* 11(1): 83–91.

Crook, Jonathan. 2006. "Household debt demand and supply: A cross-country comparison." In *The Economics of Consumer Credit.* , ed. Giuseppe Bertola, Richard Disney and Charles Grant, 63–92. MA:MIT Press Cambridge.

Debortoli, Davide, and Jordi Galí. 2017. "Monetary policy with heterogeneous agents: Insights from TANK models." *Manuscript.*

Doepke, Matthias, and Martin Schneider. 2006. "Inflation and the redistribution of nominal wealth." *Journal of Political Economy* 114(6): 1069–1097.

Dolado, Juan, Gergo Motyovszki, and Evi Pappa. 2018. "Monetary policy and inequality under labor market frictions and capital-skill complementarity." *Manuscript.*

Dynan, Karen E., Jonathan Skinner, and Stephen P. Zeldes. 2004. "Do the rich save more?" *Journal of Political Economy* 112(2): 397–444.

Fernald, John. 2014. "A quarterly, utilization-adjusted series on total factor productivity." Federal Reserve Bank of San Francisco Working Paper 2012–19.

Frank, Mark, Estelle Sommeiller, Mark Price, and Emmanuel Saez. 2015. "Frank-Sommeiller-Price series for top income shares by US states since 1917." *WTID Method-*

ological Notes.

Galí, Jordi. 2015. *Monetary policy, inflation, and the business cycle.* Princeton University Press.

Galí, Jordi, J. David López-Salido, and Javier Vallés. 2007. "Understanding the effects of government spending on consumption." *Journal of the European Economic Association* 5(1): 227–270.

Gilchrist, Simon, and Egon Zakrajšek. 2012. "Credit spreads and business cycle fluctuations." *American Economic Review* 102(4): 1692–1720.

Goldin, Claudia Dale, and Lawrence F. Katz. 2009. *The Race between Education and Technology.* Harvard University Press.

Gornemann, Nils, Keith Kuester, and Makoto Nakajima. 2016. "Doves for the rich, hawks for the poor? Distributional consequences of monetary policy." *Manuscript.*

Gorodnichenko, Yuriy, and Byoungchan Lee. 2019. "Forecast Error Variance Decompositions with Local Projections." *Journal of Business & Economic Statistics,* forthcoming.

Griffin, Peter. 1992. "The impact of affirmative action on labor demand: A test of some implications of the Le Chatelier principle." *Review of Economics and Statistics* 251–260.

Guerrieri, Veronica, and Guido Lorenzoni. 2017. "Credit crises, precautionary savings, and the liquidity trap." *Quarterly Journal of Economics* 132(3): 1427–1467.

Guiso, Luigi, and Paolo Sodini. 2013. "Household finance: An emerging field." In *Handbook of the Economics of Finance.* Vol. 2, 1397–1532. Elsevier.

Guvenen, Fatih, Fatih Karahan, Serdar Ozkan, and Jae Song. 2015. "What do data on millions of US workers reveal about life-cycle earnings risk?" National Bureau of Economic Research Working Paper 20913.

Guvenen, Fatih, Sam Schulhofer-Wohl, Jae Song, and Motohiro Yogo. 2017. "Worker betas: Five facts about systematic earnings risk." *American Economic Review: Papers & Proceedings* 107(5): 398–403.

Guvenen, Fatih, Serdar Ozkan, and Jae Song. 2014. "The nature of countercyclical income risk." *Journal of Political Economy* 122(3): 621–660.

Heer, Burkhard, and Christian Scharrer. 2016. "The Burden of Unanticipated Government Spending." CESifo Working Paper 5876.

Huang, Kevin X.D., and Zheng Liu. 2002. "Staggered price-setting, staggered wage-setting, and business cycle persistence." *Journal of Monetary Economics* 49(2): 405–433.

Johnson, David S., Jonathan A. Parker, and Nicholas S. Souleles. 2006. "Household expenditure and the income tax rebates of 2001." *American Economic Review* 96(5): 1589–1610.

Jordà, Òscar. 2005. "Estimation and inference of impulse responses by local projections." *American Economic Review* 95(1): 161–182.

Jurado, Kyle, Sydney C. Ludvigson, and Serena Ng. 2015. "Measuring uncertainty." *American Economic Review* 105(3): 1177–1216.

Kaplan, Greg, and Giovanni L. Violante. 2014. "A model of the consumption response to fiscal stimulus payments." *Econometrica* 82(4): 1199–1239.

Kaplan, Greg, and Giovanni L. Violante. 2018. "Microeconomic Heterogeneity and

Macroeconomic Shocks." *Journal of Economic Perspectives* 32(3): 167–194.

Kaplan, Greg, Benjamin Moll, and Giovanni L. Violante. 2018. "Monetary policy according to HANK." *American Economic Review* 108(3): 697–743.

Kaplan, Greg, Giovanni L. Violante, and Justin Weidner. 2014. "The wealthy hand-to-mouth." *Brookings Papers on Economic Activity* 1: 77–138.

Kilian, Lutz. 2008. "Exogenous oil supply shocks: how big are they and how much do they matter for the US economy?" *Review of Economics and Statistics* 90(2): 216–240.

Krueger, Dirk, Kurt Mitman, and Fabrizio Perri. 2016. "Macroeconomics and household heterogeneity." In *Handbook of Macroeconomics.* Vol. 2, 843–921. Elsevier.

Krusell, Per, Lee E. Ohanian, José-Víctor Ríos-Rull, and Giovanni L. Violante. 2000. "Capital-skill complementarity and inequality: A macroeconomic analysis." *Econometrica* 68(5): 1029–1053.

Kuhn, Moritz, and José-Victor Rios-Rull. 2016. "2013 Update on the US earnings, income, and wealth distributional facts: A View from Macroeconomics." *Federal Reserve Bank of Minneapolis Quarterly Review* 37(1): 1–75.

Kwiatkowski, Denis, Peter C.B. Phillips, Peter Schmidt, and Yongcheol Shin. 1992. "Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?" *Journal of Econometrics* 54(1-3): 159–178.

Lorenzoni, Guido. 2009. "A theory of demand shocks." *American Economic Review* 99(5): 2050–84.

McKay, Alisdair, and Ricardo Reis. 2016. "The role of automatic stabilizers in the US business cycle." *Econometrica* 84(1): 141–194.

McKay, Alisdair, Emi Nakamura, and Jón Steinsson. 2016. "The power of forward guidance revisited." *American Economic Review* 106(10): 3133–58.

McKay, Alisdair, Emi Nakamura, and Jón Steinsson. 2017. "The discounted euler equation: A note." *Economica* 84(336): 820–831.

Mian, Atif, and Amir Sufi. 2015. *House of debt.* University of Chicago Press.

Mian, Atif, Kamalesh Rao, and Amir Sufi. 2013. "Household balance sheets, consumption, and the economic slump." *Quarterly Journal of Economics* 128(4): 1687–1726.

Nakamura, Emi, and Jon Steinsson. 2014. "Fiscal stimulus in a monetary union: Evidence from US regions." *American Economic Review* 104(3): 753–92.

Pagan, Adrian. 1984. "Econometric issues in the analysis of regressions with generated regressors." *International Economic Review* 25(1): 221–247.

Parker, Jonathan A., and Annette Vissing-Jorgensen. 2009. "Who bears aggregate fluctuations and how?" *American Economic Review: Papers & Proceedings* 99(2): 399–405.

Parker, Jonathan A., Nicholas S. Souleles, David S. Johnson, and Robert McClelland. 2013. "Consumer spending and the economic stimulus payments of 2008." *American Economic Review* 103(6): 2530–53.

Piketty, Thomas, and Emmanuel Saez. 2003. "Income inequality in the United States, 1913–1998." *Quarterly Journal of Economics* 118(1): 1–41.

Ragot, Xavier. 2018. "Heterogeneous agents in the macroeconomy: reduced-heterogeneity representations." In *Handbook of Computational Economics*. Vol. 4, 215–253. Elsevier.

Ramey, Valerie A., and Sarah Zubairy. 2018. "Government spending multipliers in good times and in bad: evidence from US historical data." *Journal of Political Economy* 126(2): 850–901.

Ravn, Morten O., and Vincent Sterk. 2017. "Job uncertainty and deep recessions." *Journal of Monetary Economics* 90: 125–141.

Ravn, Morten O., and Vincent Sterk. 2018. "Macroeconomic fluctuations with HANK & SAM: An analytical approach." *Manuscript*.

Romer, Christina D., and David H. Romer. 1999. "Monetary Policy and the Well-Being of the Poor." *Federal Reserve Bank of Kansas City Economic Review* 84(1): 21–49.

Romer, Christina D., and David H. Romer. 2004. "A new measure of monetary shocks: Derivation and implications." *American Economic Review* 94(4): 1055–1084.

Rotemberg, Julio J. 1982. "Sticky prices in the United States." *Journal of Political Economy* 90(6): 1187–1211.

Rotemberg, Julio J., and Michael Woodford. 1997. "An optimization-based econometric framework for the evaluation of monetary policy." *NBER Macroeconomics Annual* 12: 297–346.

Rothschild, Michael, and Joseph E Stiglitz. 1970. "Increasing risk: I. A definition." *Journal of Economic Theory* 2(3): 225–243.

Rothschild, Michael, and Joseph E Stiglitz. 1971. "Increasing risk: II. Its economic consequences." *Journal of Economic Theory* 3(1): 66–84.

Saez, Emmanuel, and Gabriel Zucman. 2016. "Wealth inequality in the United States since 1913: Evidence from capitalized income tax data." *Quarterly Journal of Economics* 131(2): 519–578.

Smets, Frank, and Rafael Wouters. 2007. "Shocks and frictions in US business cycles: A Bayesian DSGE approach." *American Economic Review* 97(3): 586–606.

Song, Jae, David J. Price, Fatih Guvenen, Nicholas Bloom, and Till Von Wachter. 2018. "Firming up inequality." *Quarterly Journal of Economics* 134(1): 1–50.

Storesletten, Kjetil, Chris I. Telmer, and Amir Yaron. 2004. "Cyclical dynamics in idiosyncratic labor market risk." *Journal of Political Economy* 112(3): 695–717.

Straub, Ludwig. 2018. "Consumption, Savings, and the Distribution of Permanent Income." *Manuscript*.

Wolff, Edward N. 2017. "Household Wealth Trends in the United States, 1962 to 2016: Has Middle Class Wealth Recovered?" National Bureau of Economic Research Working Paper 24085.

Woodford, Michael. 2003. *Interest and prices.* Princeton University Press.

Yellen, Janet L. 2016. "Macroeconomic research after the crisis." *Speech given at the 60th Annual Economic Conference, Federal Reserve Bank of Boston,* Boston, October 14.

Zidar, Owen M. 2019. "Tax cuts for whom? Heterogeneous effects of income tax changes on growth and employment." *Journal of Political Economy* 127(3): 1437–1472.

Table 1: Summary statistics.

	1975:q1	1984:q1	2001:q1	2014:q1
Industrial classification	SIC 2-digit	SIC 4-digit	NAICS 6-digit	NAICS 6-digit
Number of cells	105,026	219,300	265,805	268,875
Total number of workers, million	59.9	64.8	89.0	96.3
Total quarterly earnings, USD billion	145.5	297.6	846.4	1,303.4
Average quarterly earnings, USD	2,430	4,590	9,514	13,540
Distributions of the number of workers in a cell				
P1	1	1	1	1
P25	24	18	23	23
P50	78	51	64	66
P75	280	167	207	214
P99	8,750	4,109	4,543	4,948

Notes: A cell means an industry/county/ownership-type combination in the QCEW, where the ownership code differentiates establishments owned privately, by a local government, by the federal government, and by an international government. Because the number of workers is counted in each month in this dataset, I use the average number of workers over three months in each cell. The earnings are pretax and available at a quarterly frequency. As shown in the upper half of the table, the number of cells is far greater than the sample size of a typical survey. Furthermore, the size of most of the cells is small. For example, there are approximately 66 workers in a median-sized cell in the first quarter of 2014, which corresponds to only 0.00007% of the total number of workers in the same period.

Table 2: Model parameters.

Parameter	Value	Description, Source, and Comment
β	0.99	Time preference
γ^K	8.53^e	Coefficient of RRA for the Keynesian at the SS: $\gamma^K/(1-b^K)$
b^K	0	Consumption habits for the Keynesian$^{(1)}$
γ^R	2	Coefficient of RRA for the Ricardian at the SS$^{(2)}$: $\gamma^R/(1-b^R)$
b^R	0.7	Consumption habits for the Ricardian$^{(2)}$
$\bar{u}^K_C/\bar{u}^R_C$	3.83^e	Ratio of the marginal consumption utilities at the SS
$\bar{s}^K$	0.2	Population share of the Keynesian family at the SS$^{(3)}$
$\bar{s}^K_C$	0.11	Consumption share of the Keynesian family at the SS$^{(4)}$
$\bar{s}^K_N$	0.08	Labor share of the Keynesian family at the SS$^{(5)}$
q^{RK}	0.0025	Transition probability from the Ricardian to the Keynesian family
η_Y	4.38^e	Negative elasticity of q^{KK}_t with respect to Y_t (Equation (10))
η_s	0.53^e	Negative elasticity of q^{KK}_t with respect to s^K_{t-1} (Equation (10))
φ	1/0.54	Elasticity of labor disutility at the SS$^{(6)}$
δ	0.025	Capital depreciation rate
α	2/3	Production function: $Y = AK^{1-\alpha}N^{\alpha}$.
$\Phi^{\nu}_{\nu\nu}(\bar{\nu})$	0.21^e	Second derivative of the capital utilization costs at the SS$^{(7)}$
$\Phi^{I}_{II}(1)$	1.65^e	Second derivative of the investment adjustment costs at the SS
$\mathcal{M}_P$	1.2	Gross price markup at the SS$^{(8)}$
ψ_P	233.3	Price adjustment costs. Equivalent to a Calvo probability of 0.75.
$\mathcal{M}_W$	1.2	Gross wage markup at the SS$^{(9)}$
ψ_W	706.3	Wage adjustment costs. Equivalent to a Calvo probability of 0.75.
ϕ_C	0.6	$\bar{C}/\bar{Y}$.
ϕ_I	0.2	$\bar{I}/\bar{Y}$. $\phi_G \equiv \bar{G}/\bar{Y} = 0.2$.
ρ_i	0.9	Monetary policy: interest rate smoothing (Equation (14))
ζ_π	2	Monetary policy: responsiveness to price inflation (Equation (14))
ζ_Y	0.15	Monetary policy: responsiveness to output (Equation (14))
ρ_Z	0.78^e	Persistence of redistribution shocks
ρ_A	0.81^e	Persistence of productivity shocks
ρ_G	0.97	Persistence of government expenditure shocks$^{(10)}$
σ_Z	0.0028^e	Standard deviation of redistribution shocks
σ_i	0.0008^e	Standard deviation of monetary policy shocks
σ_A	0.0094^e	Standard deviation of productivity shocks
σ_G	0.0050	Standard deviation of government expenditure shocks$^{(10)}$

Notes: e: estimated, posterior mode. SS: steady state. (1) The pre-MCMC numerical optimization returns 0. (2) The labor unions share the same parameters. (3) Debortoli and Galí (2017). (4) Krueger, Mitman and Perri (2016). (5) Kuhn and Rios-Rull (2016). (6) Chetty et al. (2011). (7) The first derivative, $\Phi^{\nu}_{\nu}(\bar{\nu}) = 0.035$, is chosen to make $\bar{\nu} = 1$. (8) Rotemberg and Woodford (1997). (9) Griffin (1992) and Huang and Liu (2002). (10) Smets and Wouters (2007).

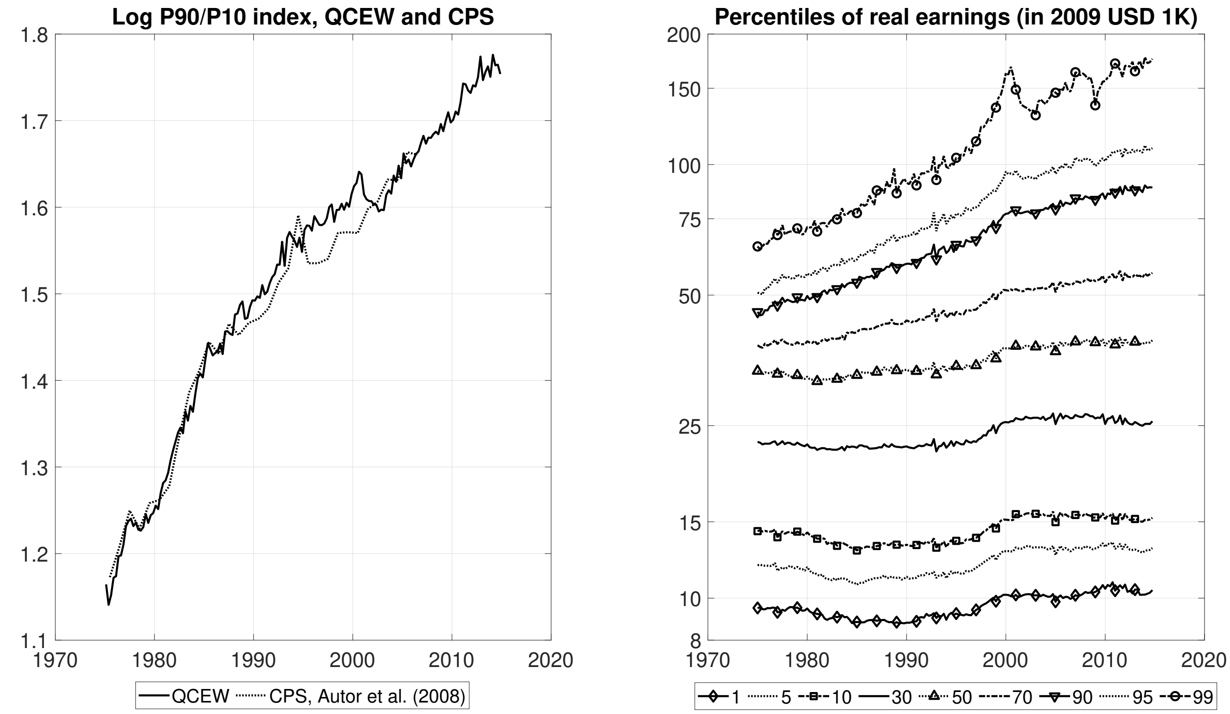

Figure 1: The new quarterly inequality index and percentiles of real earnings.

Notes: The left panel depicts my new, quarterly inequality index in comparison with an annual measure based on individual-level data. The latter is constructed by Autor, Katz and Kearney (2008), using the March annual demographic survey in the CPS. Note that the two series have similar values and historical patterns. The right panel shows selected percentiles of the real earnings distribution (annualized) in logarithmic scale. Each percentile is deflated using the GDP implicit deflator.

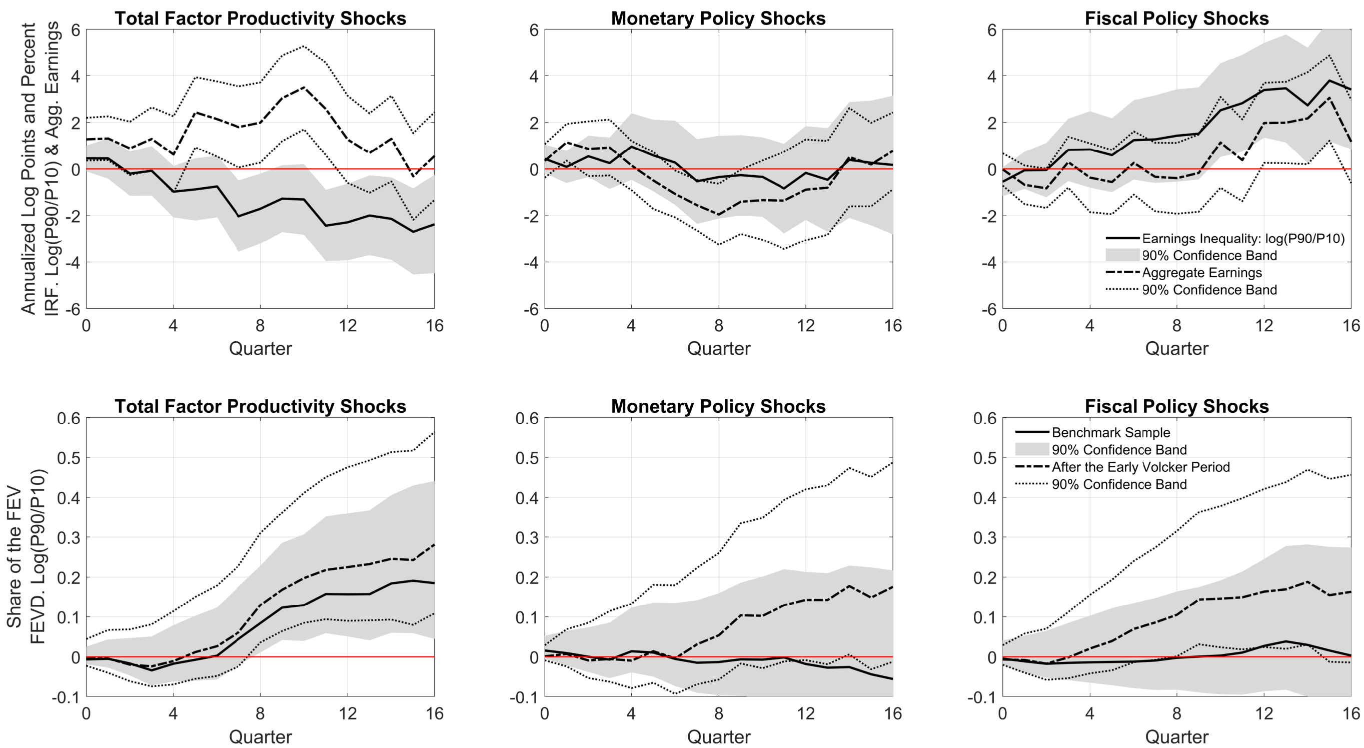

Figure 2: Effects of structural shocks on earnings inequality and aggregate earnings (IRFs and FEVDs).

Notes: The upper three panels show the IRFs of the inequality index and aggregate real earnings. I consider one-standard-deviation shocks to TFP, MP, and FP. The units are annualized log points and percentages. Robust standard errors are used. Because the KPSS test does not reject the null of trend-stationarity for aggregate real earnings, I include the $d_h t$ term and substitute y_{t-i} for Δy_{t-i} in Equation (1) (Kwiatkowski et al., 1992). The benchmark result is not sensitive to the specification details. See Appendix B.3 for results based on other lag lengths, other inequality measures, specifications controlling for the early Volcker period, a model with an oil supply shock of Kilian (2008), and IRFs estimated in a shock-by-shock manner. The lower panels illustrate the FEVDs of the inequality index. Because of the bias-correction step in the estimator of Gorodnichenko and Lee (2019), the estimates can be negative, indicating a minimal contribution of the shock of interest to the forecast error variance. The benchmark sample spans from 1978:q1 to 2008:q4, where I also show the estimates based on the sample from 1983:q1. This is because the FEVDs for FP shocks are sensitive to several observations during the early Volcker period. See Appendix B.4 for an extensive robustness check.

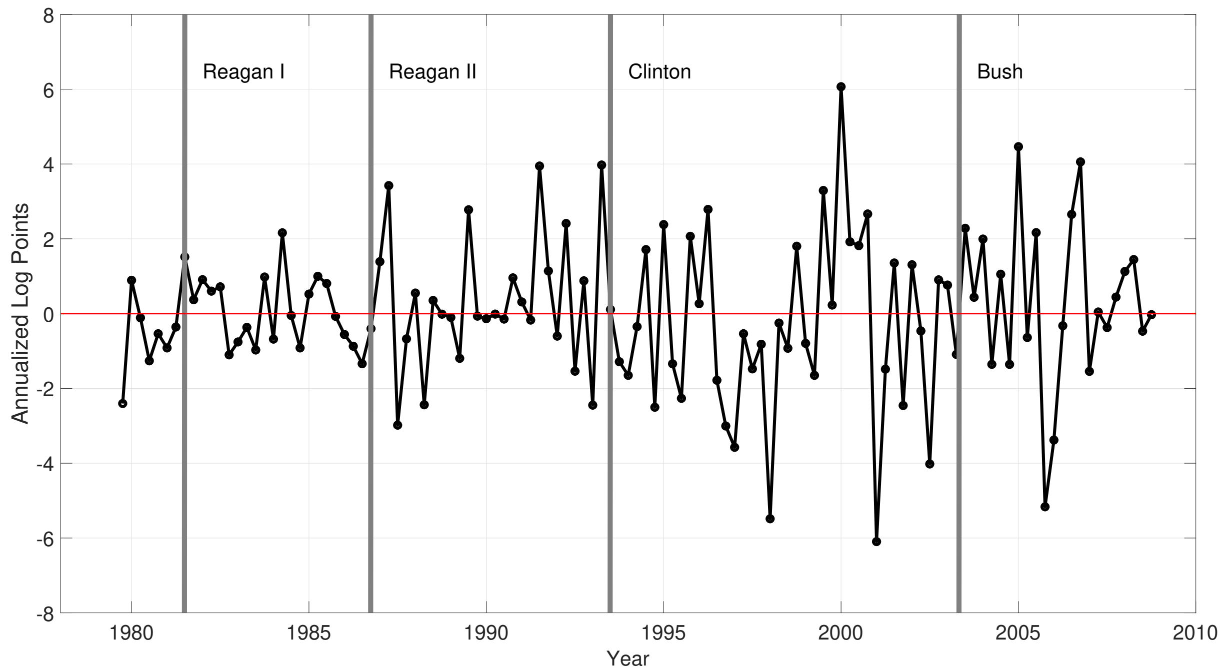

Figure 3: Identified unanticipated innovations in earnings inequality.

Notes: This figure plots the unanticipated innovations in earnings inequality, $x_{t,ineq}$, in Equation (3). The grey bars depict major tax reforms in the U.S. The name of each reform, the exact date when it was signed into law, and the president at the time are as follows: (i) the Economic Recovery Tax Act of 1981 (ERTA 81), August 13, 1981, Ronald Reagan; (ii) the Tax Reform Act of 1986 (TRA 86), October 22, 1986, Ronald Reagan; (iii) the Omnibus Budget Reconciliation Act of 1993 (OBRA 93), August 10, 1993, Bill Clinton; and (iv) the Jobs and Growth Tax Relief Reconciliation Act of 2003 (JGTRRA 03), May 28, 2003, George W. Bush. OBRA 93 raised the top marginal income tax rates, while the others did the opposite. For example, TRA 86 reduced the top marginal income tax rate from 50% to 28% effective from tax year 1987. Piketty and Saez (2003) note that the earnings distribution widened as a result. Consistently, $x_{t,ineq}$ is positive in 1987:q1. A similar relationship between the signs of $x_{t,ineq}$ and narratives of tax changes hold for the other tax reforms above.

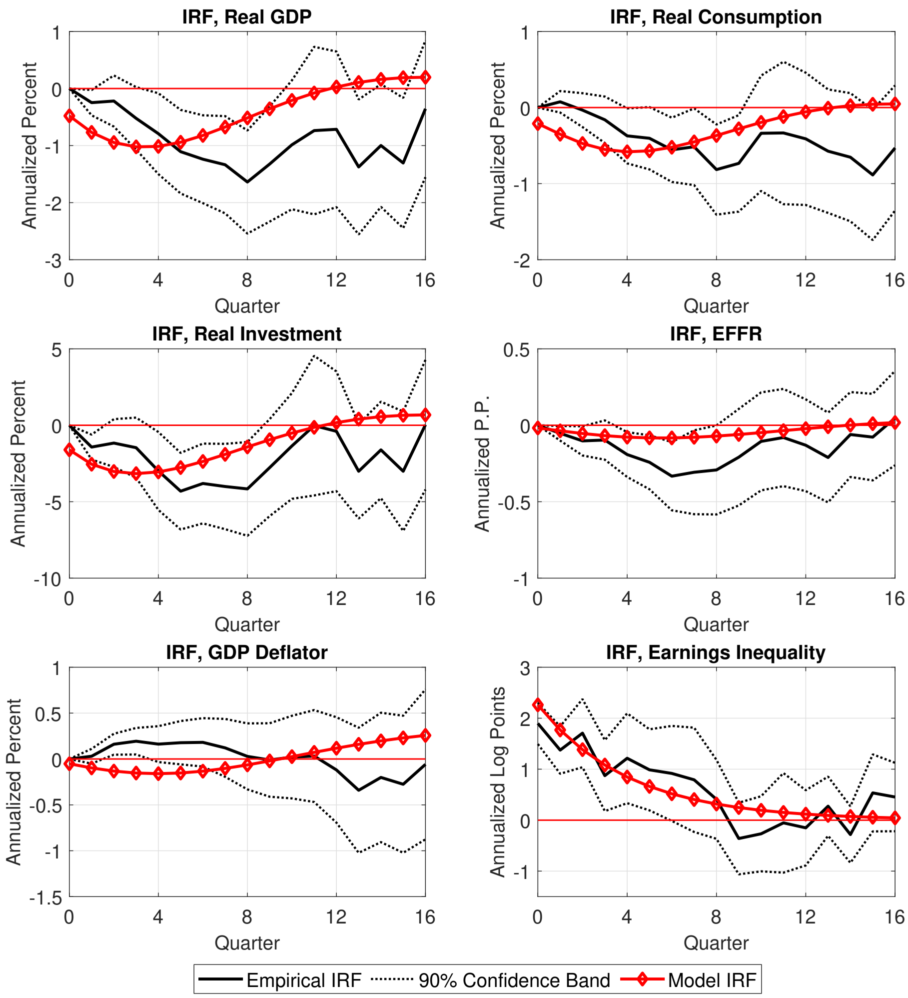

Figure 4: Responses of macroeconomic variables to redistribution shocks.

Notes: The empirical IRFs are estimated using local projections in Equation (4). The impulse is a one-standard-deviation unanticipated innovation that increases earnings inequality, $x_{t,ineq}$. The bottom-right panel illustrates the response of the log P90/P10 index, y_t. I compute robust standard errors and plot the 90% confidence band. The signs and shapes of the IRFs imply that this shock substantially reduces aggregate demand in a U-shaped manner. Furthermore, the negative responses of the GDP deflator after 3 to 4 years become statistically significant when I use the sample after the early Volcker period. This result is robust to various specification details (see Appendix C.2). For the theoretical IRFs, I evaluate the THINK model at the posterior mode, shown in Table 2. Following the discussion in Section 5.2.2, I plot $-2E_t\left[\check{Z}^K_{t+h}\right] \times 400$ for the model-based responses of earnings inequality. Note that the peak effects of both the empirical and model responses are similar. Furthermore, the model responses are in the 90 percent confidence bands at most lags. Although this is not the case for small hs, the moment conditions for $h < 4$ are not considered when evaluating the posterior, as discussed in Section 5.2.2. This is because the contemporaneous empirical responses for the above variables (except for y_t) are zero by construction, which further affect estimates for small hs.

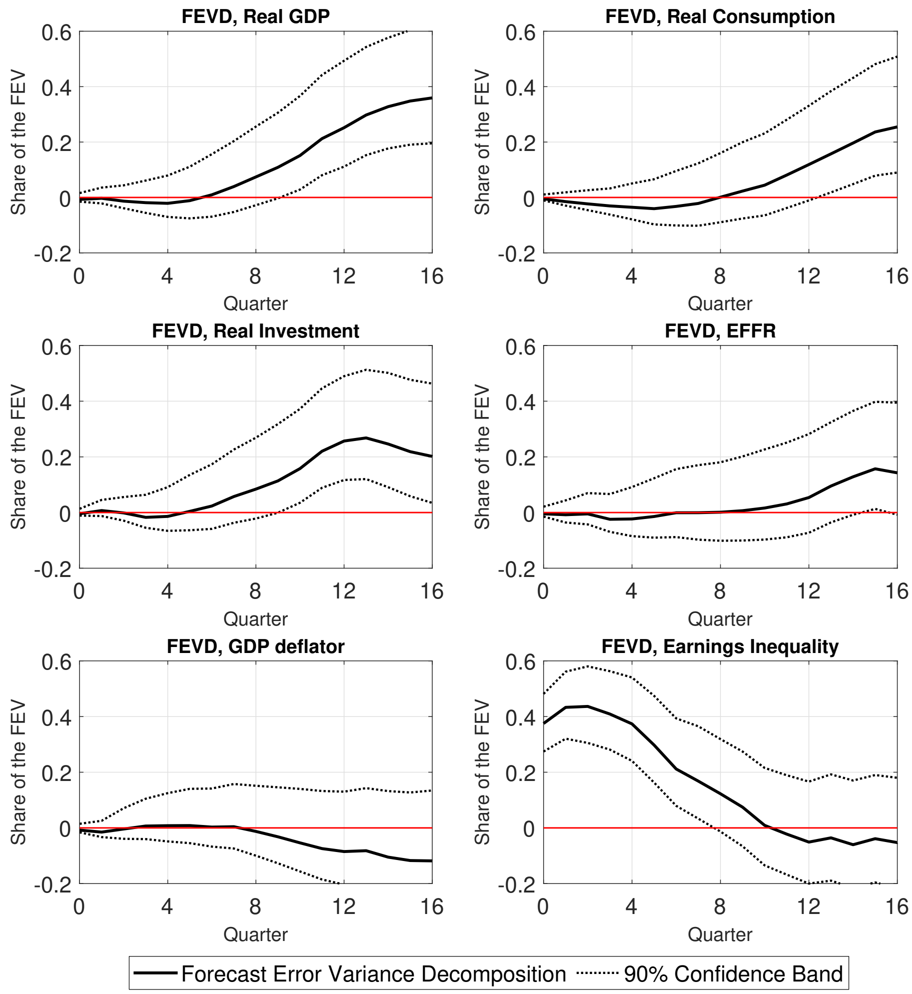

Figure 5: FEVDs of macroeconomic variables.

Notes: I employ the bias-corrected R^2 estimator of Gorodnichenko and Lee (2019) to estimate the FEVDs in relation to unanticipated innovations in earnings inequality. Because of the bias-correction step in the estimator, the estimates can be negative, indicating a minimal contribution of the shock of interest to the forecast error variance. The 90 percent bootstrapped confidence bands are denoted by the dotted lines. The estimate for real GDP at a four-year horizon is 35 percent with the lower bound of its 90 percent confidence interval being approximately 20 percent. For real consumption and investment, the estimates are 25 and 20 percent at a four-year horizon, respectively. This result implies that redistributive forces may be an important source of aggregate fluctuations. On the other hand, the EFFR and GDP deflator are mostly driven by other factors. Finally, the unanticipated innovations in earnings inequality explain large variations in the log P90/P10 index in the short run. These results are not sensitive to the specification details (see Appendix C.3).

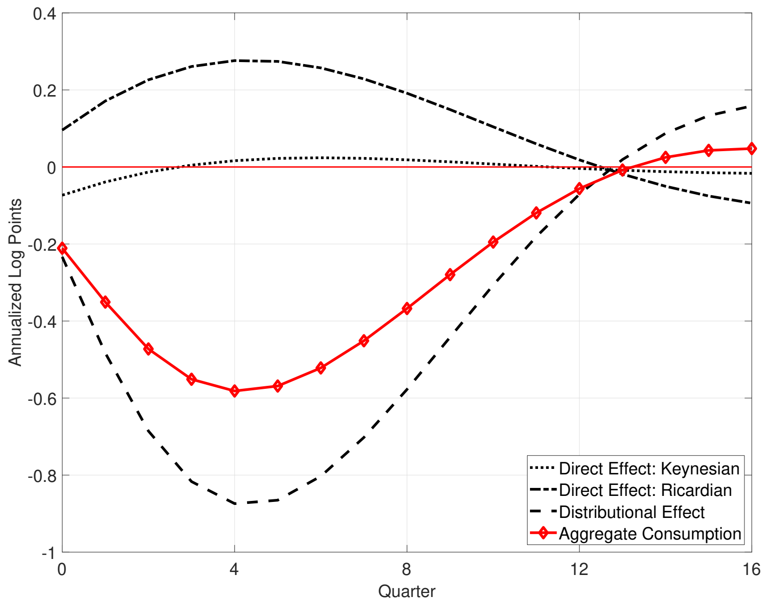

Figure 6: The decomposition of aggregate consumption responses.

Notes: This decomposition shows how different terms in Equation (17) respond to a one-standard-deviation redistribution shock in the THINK model. The dotted line represents the direct effect on Keynesian consumption, $E_t\left[\bar{s}_C^K \check{C}_{t+\tau}^K\right]$. The dash-dot line is for the direct effect on Ricardian consumption, $E_t\left[\bar{s}_C^R \check{C}_{t+\tau}^R\right]$. The distributional effect, $E_t\left[\left(\bar{s}_C^K - \frac{\bar{s}^K}{\bar{s}^R}\bar{s}_C^R\right)\check{s}_{t+\tau}^K\right]$, is illustrated by the dashed line. The responses of aggregate consumption, $E_t\left[\check{C}_{t+\tau}\right]$, are shown by the red solid line with diamonds. The units are annualized percent, obtained by multiplying the model outcome by 400. It is clear that the negative, U-shaped responses of aggregate consumption are mostly driven by the distributional effects.

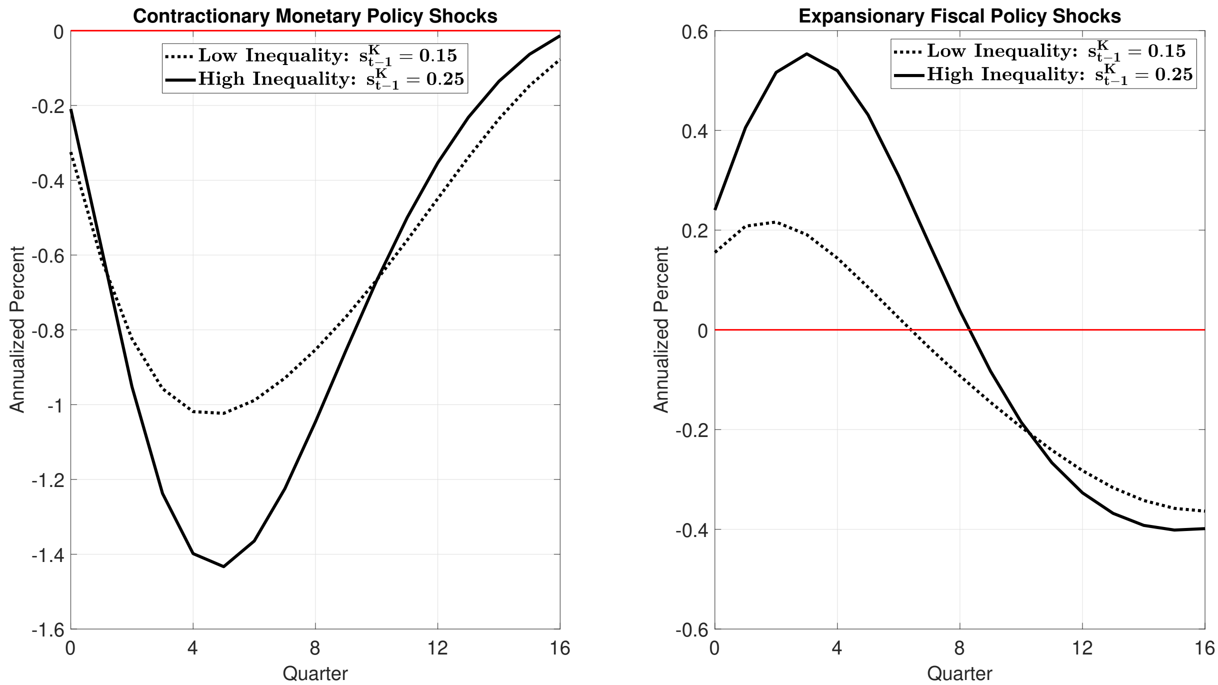

Figure 7: Theoretical responses of consumption, conditioned on the level of inequality.

Notes: Following Andreasen, Fernández-Villaverde and Rubio-Ramírez (2017), the generalized impulse responses are computed using the third-order pruned state-space system. In the high inequality state, $s^K_{t-1} = 0.25$, and all the other variables equal their steady-state values. The low-inequality state is based on $s^K_{t-1} = 0.15$. The impulses are one-standard-deviation contractionary monetary policy shocks and expansionary fiscal policy shocks. The units for the responses are annualized percent. It is evident that stabilization policies are more powerful in the high-inequality state than in the low-inequality state. The results for the other variables are similar (Appendix E.1).

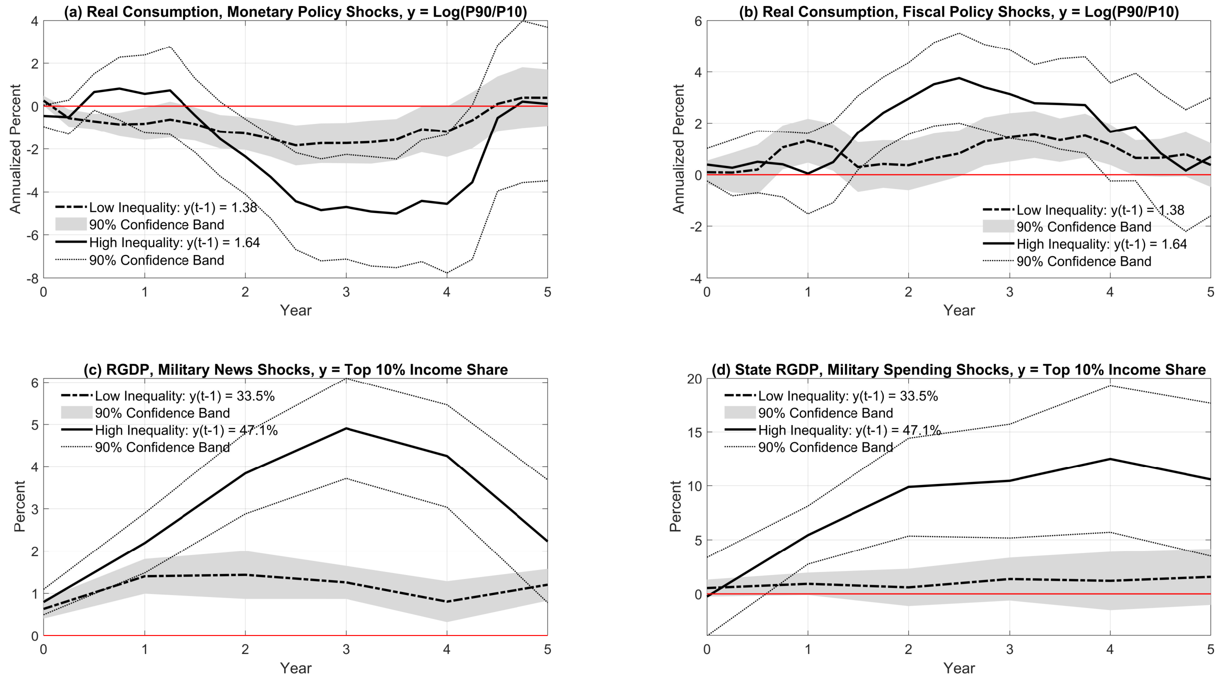

Figure 8: Empirical responses of consumption or GDP, conditioned on the level of inequality.

Notes: Panels (a) and (b) depict the generalized impulse response functions (GIRFs) of consumption given a one-standard-deviation contractionary monetary policy shock and an expansionary fiscal policy shock. I use recent data spanning from 1978:q1 to 2008:q4, as discussed in Section 6.2.1. Each panel plots two GIRFs, conditioned on the value of the log P90/P10 index being one standard deviation below or above the mean, 1.38 and 1.64, respectively. For the responses of other macroeconomic variables and results based on total factor productivity shocks, see Appendix E.2. The results in panel (b) are based on the long historical data of Piketty and Saez (2003) and Ramey and Zubairy (2018), where the sample period is from 1917 to 2015. Important for my identification, the top 10% income share displays a U-shaped pattern during the sample periods. The impulse is a military news shock from Ramey and Zubairy with a present discounted value amounting to 10 percent of trend GDP. I plot the GIRFs of real GDP, conditioned on the top 10% income share being 33.5% and 47.1%, as in 1980 and 2010, respectively. The result for the GDP deflator and unemployment rate and further robustness checks are shown in Appendix E.3. Finally, I compare U.S. states with different levels of inequality. I show the responses of state real GDP to a military spending shock that amounts to 1% of state GDP. I use Equation (20) in Section 6.2.3 to estimate the GIRFs, conditioned on the top 10% income share by state. It is clear that all the results above imply that the power of stabilization policies increases with the level of inequality. Economic output responds more strongly when earnings and income are more unequally distributed.