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Essays on The Economic Effects of Income Inequality

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ESSAYS ON THE ECONOMIC EFFECTS OF INCOME INEQUALITY

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To: Dean John F. Stack, Jr.
Steven J. Green School of International and Public Affairs

This dissertation, written by Adir dos Santos Mancebo Junior, and entitled Essays on the Economic Effects of Income Inequality, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

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DEDICATION

To God. It is all His. To my wonderful wife, Raphaela. I would not have finished this work without your immense love and support. Thank you for being so good to me. I also dedicate this to my parents, Adir and Valeria, my sister, Nathalia, many family members, and friends who supported me with prayers and words of encouragement.

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ABSTRACT OF THE DISSERTATION

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Income inequality has been rising throughout the world. In the United States, for example, the income share of the population at the top 10% of the income distribution rose 34% from 1980 to 2019 according to data from the World Inequality Database. This dissertation studies how increasing levels of income inequality might affect the economy.

In the first chapter, I show that changes in the level of income inequality may affect consumption volatility through changes in household aggregate marginal propensity to consume (MPC). I propose a simple theoretical framework to explain this dynamic and evaluate it empirically, combining data from the Panel Study of Income Dynamics and from the Census Bureau's Annual Social and Economic supplement of the Current Population Survey. This is the first study to estimate US state-level measures of average and aggregate MPC out of labor income. I find that the average MPC increases as the level of average state income inequality increases and that among households of the same income level, household MPC is higher in states with more income inequality. I also find that if the covariance term of a state's aggregate MPC is positive, higher inequality increases its amplification effect; similarly, higher inequality increases the dampening effect of the covariance term in states with negative covariance. Given these results, I estimate a panel data model using US state-level aggregate data and find that, overall, when there is a shock in

aggregate GDP, higher inequality is associated with bigger fluctuations in aggregate consumption.

The second chapter uses annual US county-level data from 2007 to 2015 to empirically investigate if an increase in income inequality affects house prices. I determine that higher inequality is positively correlated with prices measured by the Zillow index. A 1% increase in the county Gini coefficient is associated with a 0.04% increase in the average price of all houses. A rise in the inequality measure is also associated with increases of approximately 0.03% in the prices of bottom- and top-tier houses separately. When an interaction term between the Gini coefficient and mortgage interest rates is added to the empirical model, the overall positive relationship between inequality and housing prices is driven by an interest rate channel. Hence, I propose a simple theoretical framework to explain this phenomenon.

In the last chapter, I explore the common currency union formed by US states to examine how higher income inequality affects monetary policy effectiveness. I start the investigation with a cross-sectional analysis and find no statistically significant difference between the response of personal income and private employment in states with low and high historical levels of income inequality between 1990 and 2007. However, using quarterly US state-level Gini coefficients in a panel version of a local projection estimation, I contend that a one-percentage-point increase in the Gini coefficient is associated with a smaller change in both state personal income and private employment when a monetary policy shock hits the economy. The initial effect is small but significant and increases over time.

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INTRODUCTION

The main purpose of this dissertation is to rigorously investigate how rising income inequality affects the economy through neglected or not well-understood channels.

In the past decade, a renewed interest in the topic of inequality has emerged among economists. The main catalyst for this phenomenon was the Great Recession of 2008–2009, which occurred after many years of rising income and wealth inequality, especially among advanced economies. Interested in the possible connection between these two events, numerous scholars dedicated their research to better understanding how increasing income inequality affects the economy. Their findings have shown, for example, that high household leverage and crises can be caused by changes in the income distribution (Kumhof et al., 2015), that higher inequality reduces the effectiveness of fiscal policy (Brinca et al., 2016), and that increasing income disparities change consumer behavior (Jappelli & Pistaferri, 2014).

Nonetheless, there is still much to be understood about the possible consequences for the economy due to rising income inequality. This work is an attempt to advance such knowledge and bring more clarity to this issue. Accordingly, I use state- and county-level data from the United States to investigate three distinct possible effects of increased inequality in the economy. First, I analyze how changes in the level of income inequality might affect consumption volatility through changes in household aggregate marginal propensity to consume (MPC). Then I examine the relationship between income inequality and house prices. Finally, I estimate the impact of rising income inequality on monetary policy effectiveness.

In the first essay, I demonstrate how changes in income inequality can affect an economy's consumption volatility via changes in household average and aggregate MPC. This relationship emerges from the fact that average and aggregate MPCs are dependent on the economy's income distribution. It is easy to show that when all output is earned by workers, the income-weighted aggregate MPC is the sum of the income-weighted average level of household MPCs and the income-weighted covariance between household MPCs and the elasticities of household incomes relative to aggregate fluctuations. As income inequality increases, these measures are affected, but the sign of the relationship is theoretically ambiguous. Therefore, I implement a meticulous empirical analysis to assess how aggregate consumption volatility is influenced by changes in household income distribution.

In the second essay, I investigate how rising income inequality affects housing prices. Theoretically, the effect of inequality on the housing market could go either way. The results in the literature are also empirically inconclusive. My work contributes to the understanding of this relationship by leveraging a panel data analysis with US county-level measures covering almost a decade. The results indicate that higher income inequality is associated with higher house prices. I show that a simple model with households separated into borrowers and lenders can explain this outcome.

Finally, in the third essay, I consider the relationship between income inequality and monetary policy effectiveness. A great amount of research has been produced in the past few years evaluating how monetary policy affects inequality. However, the possible effect of rising income inequality on monetary policy has been overlooked. To better understand this relationship, I execute an empirical strategy which culminates in an analysis that uses a novel series of quarterly measures of state income inequality. I show that an increase in inequality is associated with monetary policy being less effective. The initial effect is small but significant and increases over time.

The results uncovered in this dissertation highlight the importance of income distribution for policy decisions. Changes in the level of income inequality impact different segments of the economy through a variety of channels. The present work brings more clarity to some of the effects on the economy of rising inequality, but a general equilibrium theory that incorporates the most important elements of this relationship is still missing. It is imperative that we build a clear understanding of these mechanisms to design effective policies. A negligent approach to the distribution of income in the economy leads to inefficient outcomes of economic policies.

CHAPTER 1

INCOME INEQUALITY, HOUSEHOLD HETEROGENEITY, AND CONSUMPTION VOLATILITY

1.1 Introduction

The increase in income inequality in the United States in recent decades has received a significant amount of attention and has been well documented both in academic literature and the media. According to data from the World Inequality Database, the share of pre-tax income accruing to earners in the top decile of the distribution rose 25.4% in the United States between 1970 and 2004, from 33.8% to 42.4%. During the same period, a much less studied phenomenon occurred. Gorbachev (2011) estimates that mean volatility of household food consumption in the United States increased by 21%, and volatility of nondurable consumption rose by 25%.[1] Queries can include if these two trends related, if increasing levels of income inequality contribute to more volatile average household consumption, and what the effects are on aggregate consumption.

In this chapter, I show that changes in the level of income inequality might indeed affect an economy's consumption volatility through changes in household average and aggregate MPC. When all output is earned by workers, the income-weighted aggregate MPC consists of two terms: (i) the income-weighted average level of household MPCs and (ii) the income-weighted covariance between household MPCs and the elasticities of household incomes relative to aggregate fluctuations. Thus, to empirically evaluate how increasing levels of inequality affect the household

[1] These results are obtained after accounting for predictable variations in consumption due to changes in family composition and structure, real interest rates, income uncertainty, and cash on hand (as a proxy for precautionary savings), and after controlling for measurement error in consumption, nonseparability of preferences, and liquidity constraints.

consumption response to income shocks, I combine data from the Panel Study of Income Dynamics (PSID) and the Census Bureau's Annual Social and Economic supplement of the Current Population Survey (ASEC-CPS) to estimate, for the first time, US state-level measures of average and aggregate MPC out of labor income.

I find that the average MPC increases as the level of average state income inequality increases and that among households of the same income level, household MPC is higher in states with more income inequality. I also find that if the covariance term of a state's aggregate MPC is positive, higher inequality increases its amplification effect; similarly, higher inequality increases the dampening effect of the covariance term in states with negative covariance. Given these results, I estimate a panel data model using US state-level aggregate data and find that, overall, when there is a shock in aggregate GDP, higher inequality is associated with larger swings in consumption. As expected, this effect is stronger when covariance acts as an amplification mechanism and is weaker when covariance dampens the effect of the shock. Quantitatively, the consumption response to changes in inequality is low. However, everything else constant, the state with the highest level of inequality in the data experiences a change in consumption that is, on average, double the one observed for the lowest level of inequality when there is a shock in aggregate GDP.

The starting point of the analysis is defining household average and aggregate MPC. If household MPCs are homogeneous, changes in income distribution will have no impact on overall MPC. For instance, if every household consumes 50 cents of an extra dollar received, then income-weighted average household MPC is 0.50, and even after a redistribution of income from bottom to top earners, it will still be 0.50. However, if household MPCs are heterogeneous and associated with income level, changes in the income distribution will influence average MPC, even though the characteristics of this impact may not be clear.

There is evidence in the literature — and my analysis corroborates these findings — that as household income increases, MPC decreases (e.g., Dynan et al., 2004; Johnson et al., 2006). If this is the nature of the relationship, a "mean-preserving" redistribution of income from the middle class to both low- and high-income households could affect average MPC in different ways. The magnitude and sign of a change in average MPC would depend on the household MPC distribution and the initial income share of each class of households. However, when increasing inequality is characterized by income moving from the bottom to the top of the distribution, with everything else constant, income-weighted average household MPC will decrease because a larger share of overall income is held by households with lower MPC.

I also consider another crucial effect of increasing income inequality. Higher inequality has been associated with higher credit prices and reduced access to credit for low-income households (Coibion et al., 2020). If this is indeed the case, one could argue that higher levels of income inequality should be associated with a higher share of credit-constrained households in the region. An increase in the share of constrained households would then translate into relatively more high-MPC households in the economy. That, in turn, would make the economy's aggregate MPC increase, intensifying aggregate consumption volatility, everything else remaining constant.

To investigate this mechanism, I build a simple model in the second section of this paper to formalize the connection between changes in income inequality levels and aggregate MPC. Then, to evaluate the validity of the proposed theoretical framework, I separately estimate the terms that form the aggregate MPC, namely, the average MPC and the covariance between household MPCs and the sensitivities of households' income to aggregate movements. I do so for both the United States as a whole and for each state separately. To my knowledge, this is the first study to estimate average and aggregate MPCs at the state level in the United States.

What makes it possible to conduct state-level MPC estimations is my adaptation of a novel methodology proposed by Patterson (2020), who uses a two-step strategy to estimate the MPC of US workers. I estimate the MPC for households with different demographic characteristics using the panel structure of the PSID and impute these values in the ASEC-CPS data.[2] In the first step of the estimation, an unemployment shock is used as an instrument for income shock.

Consistent with the literature, I estimate US national average MPC to be 0.41, and I find that household MPC decreases as income increases. The state-level estimations are very interesting. They range from 0.06 in North Dakota to 0.80 in the District of Columbia, with a standard deviation of 0.24 and a mean of 0.41. The average MPC values also vary by region. The Midwest has the lowest average of 0.09 and the West has by far the highest, 0.72. The Northwest and the South are in the middle, with average MPC estimates of 0.27 and 0.47, respectively. Although these results might be affected by the low number of observations in a few states, the pattern of regional average MPC is consistent with the median household debt-to-income ratio for the US regions. For instance, in 2017, the last year of the estimated period, the median household debt-to-income ratios for the West, South, Northeast, and Midwest were 1.72, 1.38, 1.34, and 1.11, respectively. These results are in line with the findings of previous studies that show higher MPCs for liquidity-constrained households.

To explore the relationship between household MPC and income inequality, and how changes in inequality affect average MPC, for each household in the data, I

[2]Bertrand and Morse (2016) have used the ASEC-CPS data to analyze household consumption inequality at the state level.

measure its position in the distribution of permanent income and categorize households into (50) quantiles. I find that both for the United States as a whole and for each state separately, the higher the permanent income quantile is, the lower the household MPC. Furthermore, supporting the claim that higher levels of income inequality are associated with a higher share of credit-constrained households in the region, I find that among households of the same income level, household MPC is higher in states with more unequal distribution of income. I also find that the average MPC increases as the level of average state income gap widens.

To estimate the covariance term of the aggregate MPC, I follow the methodology proposed by Alves et al. (2020) because it provides a link to the income inequality question analyzed in this paper. They formalize the incidence function and allocate individuals to specific groups associated with some fixed characteristics because it is not feasible to estimate the degree of exposure for each individual. Empirically, these characteristics may be represented by the permanent component of labor income. Therefore, after distributing households into 50 quantiles of permanent income, I estimate the income shares and the elasticities of each quantile. The positive covariance estimated for the United States nationally is in line with that stated in previous studies by Patterson (2020) and Alves et al. (2020).

The estimations at the state level exhibit insightful results. Several states present positive covariances, whereas others yield negative covariances. The results show that, even though at the national level the unequal incidence of shocks translates into an amplification mechanism, at the state level, some locations experience the amplification of shocks, but others undergo dampening. With regard to the relationship between income inequality and covariance, I find that if the covariance term of a state's aggregate MPC is positive, higher inequality increases its amplification effect, whereas higher inequality increases the dampening effect of the covariance term in states with negative covariance.

These results indicate that a rise in income inequality may increase aggregate MPC, mainly through an increase in average MPC. Hence, the final step of my analysis is to use aggregate data from all 50 US states plus the District of Columbia to estimate a panel data model from 1998 to 2015 to try to establish a causal effect between changes in inequality and aggregate MPC. I find that, overall, when there is a shock in aggregate GDP, higher inequality is associated with greater changes in aggregate consumption. As expected, when covariance is positive and amplifies the shock, the effect of inequality on consumption volatility is stronger than in the case of negative covariance. Still, the difference in aggregate consumption associated with changes in the level of income inequality is quantitatively small. These findings seem to corroborate the hypothesis that changes in the level of income inequality affect aggregate consumption volatility through aggregate MPC, but the effect is weak.

This analysis has important policy implications because consumption volatility has a significant welfare cost (see De Santis, 2007; Reis, 2009). Understanding the mechanisms that affect the variability of consumption can help reduce aggregate fluctuations and result in large welfare gains. To increase their reliability, monetary policy models may need to incorporate the interactions between income inequality and household consumption responses to income shocks. Moreover, a better understanding of these dynamics will provide the necessary foundation for policy makers to design more effective fiscal policies.

By introducing a comprehensive analysis of how increasing income inequality affects aggregate consumption volatility, this paper contributes to the literature on the effects of rising inequality. Recently, several researchers have focused on the possible economic effects of widening income gaps. This literature shows, for example, that increasing levels of inequality may affect economic growth (Cingano, 2014), lead to a higher probability of banking crises (Stiglitz, 2012), and change consumer behavior (Jappelli & Pistaferri, 2014).

By proposing a formal mechanism and empirical results for the relationship between changes in income distribution and fluctuations of aggregate economic activity, my analysis relates to literature originating with Pigou (1920), Keynes (1936), and Kaldor (1955). In the early twentieth century, these economists were already discussing the idea that the distribution of income is relevant to aggregate economic activity, with higher income inequality affecting aggregate demand and employment. More recently, this line of research has experienced a resurgence with Das (1993), who used time-series data from the United States to conclude that greater inequality is associated with more macroeconomic fluctuations. Later, Gavin and Hausmann (1996) showed that countries in Latin America are much more unequal and volatile than industrial economies.

Using a different approach, Alesina and Perotti (1996) have argued that greater inequality in the distribution of income generates social discontent, which in turn affects macroeconomic volatility via increased political instability. They find support for their hypothesis in the data. Moreover, Iyigun and Owen (2004) have theoretically and empirically demonstrated that in high-income countries, increased income inequality is associated with more volatility in consumption and GDP growth, whereas in lower-income countries, higher levels of income inequality are associated with lower volatility.[3]

[3] In contrast to these results, Breen and García-Peñalosa (2005) have shown that inequality in 1990 was correlated with volatility during the previous decades, but they find that measures of income distribution in the 1960s seemed not to affect subsequent output fluctuations. In addition, in a panel investigation, Konya and Mouratidis (2006) have

Even in light of potentially important effects of higher levels of income inequality on short-term macroeconomic activity, the research of such impacts has been relegated to the margins of the economic literature, but that changed after the world experienced the Great Recession of 2008–2009. After the financial crash and a few years of disappointing economic growth, many economists began to believe that the sharp decline in the world economy and its slow recovery could be associated with the increasing levels of inequality. The main paper addressing this issue is by Kumhof et al. (2015), who argue that a rise in inequality driven by an increase in the share of income going to those at the top of the income distribution induces these top earners to save more. This increased saving leads to lower interest rates, which induces poorer households to borrow more, ultimately leading to more financial fragility and a higher likelihood of a financial crisis.

More recently, Auclert and Rognlie (2018) have developed a quantitative framework to investigate how income inequality affects consumption and output. They found that changes in inequality have a very small effect on aggregate activity. In their model, an increase in income inequality depresses aggregate output because of the negative correlation between MPCs and income. However, once general equilibrium effects are taken into account, the size of this effect tends to be small. These results, in fact, are in line with the findings presented in this paper.

Other recent findings add support to the prediction that increasing income inequality might affect macroeconomic activity. Using a sample of advanced and emerging economies, Kohlscheen et al. (2021) have indicated that the higher inequality is, the deeper recessions are. Moreover, Feiveson et al. (2020) compared simulated macroeconomic outcomes from two versions of a New Keynesian model

found no evidence of a mutual relationship between inequality and volatility within a country; inequality is influenced by, but does not have a direct effect on volatility.

to illustrate how inequality can lead to more pronounced business cycle fluctuations when the effective lower bound (ELB) constraint binds. The two models differ in the degree of inequality but are otherwise identical in structure and are subject to the same macroeconomic shocks. They find that economic outcomes are significantly worse in the model with higher inequality when the ELB binds as monetary policy cannot effectively stabilize the economy. As a result, the unemployment rate is, on average, about 85% more volatile in the model with inequality.

Considering the findings of prior research, I attempt to provide a better understanding of the dynamics governing the relationship between income distribution and consumption volatility. To do so, the remainder of this chapter is organized as follows: Section 1.2 builds a simple model to formalize the connection between changes in income inequality levels and aggregate MPC. Section 1.3 estimates average household MPC and investigates its correlation with inequality. Section 1.4 estimates the covariance term of aggregate MPC and illustrates how it relates to the income distribution. Section 1.5 provides an empirical analysis of the effect of changes in the level of income inequality on changes in aggregate consumption. Finally, section 1.6 presents a conclusion.

1.2 Income Inequality and Aggregate MPC

To understand how different levels of income inequality might give rise to different responses of aggregate variables when there is a shock, we should consider an economy in which all income comes from labor earnings. Aggregate consumption and income are given, respectively, by $C = \sum_i c_i$ and $Y = \sum_i y_i$, where c_i is consumption of household i, and y_i is income of household i. When an aggregate shock hits this economy, household earnings will not be affected in the same way; thus, a change in aggregate income dY will be distributed across households in an unequal manner dy_i, and the aggregate MPC will be given by:

$$Agg.MPC = \sum_i \frac{dc_i}{dy_i}\frac{dy_i}{dY} \tag{1.1}$$

where $\frac{dc_i}{dy_i}$ is household i's MPC. Furthermore, when all income is earned by workers, Alves et al. (2020) and Patterson (2020) have shown that the aggregate MPC actually consists of two terms: (i) the income-weighted average level of household MPCs and (ii) the income-weighted covariance between household MPCs and the sensitivities of households' income to aggregate movements. To extract this from the original formula, household income elasticity to aggregate income is defined as $\gamma_i = \frac{dy_i}{dY}\frac{Y}{y_i} \approx \frac{dlogy_i}{dlogY}$. [4] When I substitute this expression back into (1.1), I get:

$$Agg.MPC = \underbrace{\sum_i \frac{y_i}{Y}\frac{dc_i}{dy_i}}_{\text{Income-weighted Avg. MPC}} + \underbrace{\widetilde{Cov}\left(\frac{dc_i}{dy_i}, \gamma_i\right)}_{\text{Income-weighted Covariance}} . \tag{1.2}$$

Given how aggregate MPC is expressed, it is clear that it might be affected by changes in the income distribution within an economy if household MPCs are not homogeneous and if an aggregate shock impacts households differently.[5] This relationship, however, will only be significant if household MPC heterogeneity is associated with household income level.

There is, indeed, ample evidence that household MPC is heterogeneous, but its relationship with household income is not as clear. The literature generally claims that MPC is substantially larger for low-wealth than for high-wealth households. For instance, Kaplan et al. (2014) have found that wealthy hand-to-mouth households, those with high illiquid wealth but little liquid savings, have the highest MPC.

[4]It should be noted that the income-weighted mean of γ_i equals 1.

[5]When there is equal incidence of a shock, which translates into $\gamma_i = 1$ for all i, then the covariance term is 0.

Carroll et al. (2017) have examined models that yield a higher MPC for low-wealth households, and Fisher et al. (2020), using panel survey data, have determined that MPC is lower for higher wealth quintiles. Comparing European countries, Carroll et al. (2014) have also provided evidence that aggregate MPC is higher in economies with extensive wealth inequality, where a larger proportion of households have little wealth. Since wealth and income inequality are highly correlated, if wealth distribution affects the level of aggregate MPC, it is safe to assume that income distribution would also have some effect, even if not as strong.

Regarding income level and its association with MPC, Dynan et al. (2004) have argued that poorer individuals have lower propensities to save (and thus higher propensities to consume) relative to both current and permanent income. Johnson et al. (2006) have evaluated the consumption response to tax rebates and found that MPC changes with income and asset levels, yielding a larger MPC for lower-income and liquidity-constrained households. Other studies, however, have found a U-shaped consumption response to transitory changes in household income relative to its position in the income distribution.[6] Misra and Surico (2011), for example, also also analyzed MPC out of tax rebates and assessed that whereas households with low income or low liquid wealth increased their expenditure by 10 to 40 cents for each dollar of rebate, high-income/high-liquid-wealth individuals spent either nothing or most of their rebate.

In light of these findings, it is reasonable to argue that changes in the income distribution in a given economy would result in a change in at least the average MPC. If there is a U-shaped relationship between household MPC and income level, then a "mean-preserving" redistribution of income from the middle class to both poor and rich households would result in a higher average MPC. A simple way to visualize

[6] See Pistaferri and Saporta Eksten (2012) for a table that lists these results.

this is to suppose that each income class of households represents one-third of the population and holds one-third of overall income. It can also be supposed that MPC for households in the middle class is half the MPC of the two other classes. If the middle class loses half of its income share to the other classes, that part of overall income is now in the hands of households with double the MPC, leading to an increase in the income-weighted average household MPC. Similarly, if the redistribution of income goes from the middle to the top, or from the middle and bottom to the top, average household MPC also increases, though at a lower amount in the latter case.

On the other hand, if household MPC is decreasing in income, a redistribution of income that is mean-preserving would not have a clear effect on average MPC. The magnitude and sign of a change in average MPC would depend on the household MPC distribution and the initial income share of each class of households. However, when increasing inequality is characterized by income moving from the bottom to the top of the distribution, with everything else constant, income-weighted average household MPC will decrease because a larger share of overall income is held by households with lower MPC.

1.2.1 The Average MPC Channel: A Simple Model

Before we formalize a simple model to better understand how changes in income inequality might affect average MPC, there is a potentially crucial aspect of this relationship that must be discussed. Using household-level debt data over 2000–2012 and local variation in inequality, Coibion et al. (2020) have found evidence that low-income households face higher credit prices and reduced access to credit as inequality increases.[7] If this is indeed the case, one could argue that higher levels of income inequality would be associated with a higher share of credit-constrained households in the region. An increase in the share of constrained households would then translate into relatively more high-MPC households in the economy. Consequently, even if income is redistributed from low- to high-MPC households, the simultaneous increase in the level of household MPCs in the lower end of the curve may be big enough to increase average MPC.

This mechanism is not yet established in the literature, and a deeper analysis of it is not within the scope of this paper. Nevertheless, I would argue that it is not a strong assumption to consider that this relationship holds. Dogra and Gorbachev (2016) have estimated that between 1983 and 2007, despite financial liberalization and the near-tripling of household debt, the proportion of liquidity-constrained households in the United States slightly increased. In all years, poorer households and those headed by single parents, black or Hispanic individuals, or individuals with low education were the most likely to be liquidity constrained. In fact, these gaps in access to credit (between rich and poor, white and black individuals and so on) has widened over time. During this same period, all measures of US income inequality increased. For instance, the share of pre-tax income accruing to earners in the top decile of the distribution rose almost 25%. These findings suggest that increasing inequality might increase the share of constrained households in the economy, which affects their ability to smooth consumption, increasing their MPCs.

Therefore, in the model that follows, which is based on the work of Iyigun and Owen (2004), I assume that this relationship holds for households in the bottom and the middle of the income distribution. I consider an economy with only three types

[7] They also build a simple theoretical model to explain their findings.

of households $i \in \{l, m, h\}$. All household income is derived from their labor. Here, we can assume that household i's time-invariant, innate efficiency units of labor, y_i, are drawn from the probability of distribution shown below:

$$y_i = \begin{cases} y_l & \text{with probability p} \\ y_m & \text{with probability (1-2p)}, \\ y_h & \text{with probability p} \end{cases} \tag{1.3}$$

where $p \leq 1/2$, $y_l < y_h$, and $y_m = (y_l + y_h)/2$. It must be noted that because ability is directly related to income under this specification, p is a direct measure of income inequality. An increase in p raises the proportion of households at the tails of the income distribution relative to the proportion who are in the middle, generating a mean-preserving increase in income inequality. This economy's total income is given by $Y = py_l + py_h + (1-2p)y_m = (2p + 1/2)(y_l + y_h)$, and the income share for low-, middle-, and high-income households is $\frac{py_l}{Y}$, $\frac{(1-2p)y_m}{Y}$, and $\frac{py_h}{Y}$, respectively.

As discussed earlier, low- and middle-income households are assumed to have MPCs, $\beta_l(p)$ and $\beta_m(p)$, respectively, that are functions of income inequality. As inequality (or p) increases, $\beta_l(p)$ and $\beta_m(p)$ also increase. Because high-income households always have access to the credit market, they exhibit invariant MPCs β_h, where $\beta_l(p) > \beta_m(p) > \beta_h$. From equation (1.2), I can write the income-weighted average household MPC as

$$\overline{MPC} = \frac{py_l\beta_l(p) + py_h\beta_h + (1-2p)y_m\beta_m(p)}{(2p + 1/2)(y_l + y_h)}. \tag{1.4}$$

To evaluate how average MPC changes when income inequality increases, I take the derivative of $\overline{MPC}$ with respect to p. The resulting equation is

$$\frac{\partial \overline{MPC}}{\partial p} = \frac{1/2 y_h \beta_h + y_l[(2p^2 + 1/2p)\beta_l'(p) + 1/2\beta_l(p)] + y_m[(1/2 + p - 4p^2)\beta_m'(p) - 3\beta_m(p)]}{(2p + 1/2)^2(y_l + y_h)}, \tag{1.5}$$

which does not have a clear sign. Since the denominator is always positive, I must analyze the numerator to understand the behavior of average MPC. A close look reveals that the term multiplying y_m will always be negative. Thus, for the whole expression to be positive, the other terms must be greater. It is not possible to find a specific condition for that without relying on a few assumptions, but several patterns can be determined. If the gap between y_l and y_h is sufficiently wide, which means a high initial level of income inequality, then average MPC and inequality are positively correlated. Moreover, if $\beta_m(p)$ is sufficiently low, close to β_h, or if $\beta_l'(p)$ and $\beta_m'(p)$ are sufficiently high, greater income inequality will lead to higher average household MPC.

1.2.2 The Covariance Channel: Amplification or Dampening?

Regarding the effect of changes in income inequality on the covariance term of aggregate MPC, the result is also nuanced. The covariance term is directly related to what is called an incidence function, which describes a rule for how a time-varying aggregate quantity is allocated across the distribution of households in the economy. Essentially, this function describes, for example, how additional aggregate income is distributed across the population if a shock in the economy causes the aggregate income to rise.[8] If the shock affects all households' income equally, then $\gamma_i = 1$ for all i in equation (1.2). In this case, the covariance term is 0. If an aggregate shock impacts households differently, then γ_i will vary across all i, and the covariance term could become either positive (amplifying the shock) or negative (dampening the shock).

As Alves et al. (2020) highlights, unequal incidence is an amplification mechanism for shocks if households that are more exposed to fluctuations in aggregate income are also those with high MPCs. If, instead, the correlation between MPCs and household exposure is negative, unequal incidence is a dampening mechanism. We can assume, for instance, that the relationship between household MPC and income level is negative and that unequal incidence amplifies a shock. Then a change in income distribution that makes it more polarized would increase the level of amplification. However, if unequal incidence dampens a shock, more inequality would increase the dampening effect of the covariance term.

Since the direction of the effect of changes in income inequality on the covariance term is not clear, the overall effect on aggregate MPC is not straightforward. When increasing inequality raises average MPC and the level of amplification, aggregate MPC increases. When higher inequality leads to lower average MPC and a larger dampening effect, aggregate MPC will decrease. Finally, when more inequality causes average MPC and the covariance term to move in opposite directions, either effect may dominate, or both may cancel each other out.

All of these scenarios are possible. This brief discussion shows that a comprehensive empirical investigation must be implemented to fully understand what kind of effect, if any, income inequality has on the volatility of aggregate consumption. Not only must average MPC and the covariance between household MPCs and their

[8] See Alves et al. (2020) for a more in-depth discussion of the incidence function.

income elasticities be estimated, but there must be a way to analyze how aggregate MPC varies with different levels of income inequality. My approach is to use US microdata to estimate state-level measures of the variables of interest because there is less heterogeneity between states than between countries, which makes cross-sectional analysis more meaningful. The next two sections, therefore, describe the estimation of aggregate MPC, starting with average MPC.

1.3 Average MPC Estimation and Analysis

1.3.1 MPC Estimation Methodology

A significant amount of literature has empirically investigated how consumption by individuals changes when they face an income shock.[9] Researchers have proposed several methodologies to estimate this relationship. Below, I mirror the implementation of Patterson (2020), who uses a two-step strategy to estimate the MPC of US workers. Her main data of interest comes from the Longitudinal Employer-Household Dynamics (LEHD) program. However, because this dataset does not allow her to observe the consumption behavior of individuals, she estimates the MPC of workers with different characteristics using the panel structure of the PSID and imputes these values in the LEHD. Like Patterson (2020), I start my analysis by estimating household MPC using the PSID (in the next section, I detail the data used) following the line of research beginning with Gruber (1997), who examines the consumption drop upon unemployment. From this, I estimate the following

[9] See Jappelli and Pistaferri (2010) and Carroll et al. (2014) for an extensive review of methodology and findings.

equation:

$$\Delta logC_{t,i} = \sum_x (\beta_x \Delta logy_{t,i} * x_{t,i} + \alpha_x x_{t-1,i}) + \delta_{t,s} + \varepsilon_{t,i}, \tag{1.6}$$

where $logC_{t,i}$ is log of total consumption of household i at time t, $logy_{t,i}$ is the log of labor earnings of household i at time t, $\delta_{t,s}$ captures state-by-year fixed effects, and $x_{t,i}$ is a vector of household characteristics.[10] Unemployment shock is used as an instrument for $\Delta y_{t,i}$. This choice of instrument is justified by its relevance to aggregate fluctuations, my main focus of analysis in this paper. As Patterson (2020, p. 13) argues, "If all aggregate fluctuations have the same persistence as unemployment, then this is exactly the correct MPC to answer the question of how the heterogeneous incidence of aggregate fluctuations affects the aggregate MPC. An MPC that is estimated using a purely transitory shock, such as a tax rebate, would fail to capture the consumption response to the type of income shocks that workers typically experience over the business cycle."

The next step is to connect the estimated MPCs to the other dataset. Patterson (2020) states that if the characteristics captured by x are all common to both the PSID and the LEHD, then using the estimated β_x, one can impute the MPC in the LEHD as:

$$\widehat{MPC}_{i,t} = \sum_x \hat{\beta}_x x_{i,t} \tag{1.7}$$

Since LEHD microdata required for my analysis is restricted for public use, I looked for an alternative that would allow for a state-level investigation. I found that Bertrand and Morse (2016) merge consumption data from the Consumer Expenditure Survey (CEX) with income data from the ASEC-CPS to implement a

[10] X includes five lagged income bins; a quadratic in age; family size; female, black, non white/non black, marital status, and four regions dummies; black interacted with age; and female interacted with black.

state-level analysis of household consumption inequality. Hence, I implement the methodology in Patterson (2020) using ASEC data from 1990 to 2017.

1.3.1.1 Assumptions for MPC Imputation

To perform the imputation, several important assumptions about the stability of the MPC estimates must be considered. Two of them are discussed in detail in Patterson (2020). First, in imposing that MPCs only vary by household demographics, I assume that household MPCs out of income fluctuations caused by unemployment shock are similar to the MPCs out of business cycle income shocks of different signs and magnitude. Second, conditional on demographics, the consumption response is assumed to be constant over the business cycle.

Furthermore, to impute an estimation from a national sample into a state-level representative sample, another assumption must be made. Using the PSID data, the most disaggregated geographic level I can use to control for when estimating household MPC is the Census's four regions. Hence, I must assume that the states within each of the regions exhibit the same demographic patterns and that households with the same characteristics residing in different states in the same region respond similarly to income shocks.

1.3.1.2 Data Description

The core estimation of household MPC uses data from the PSID. This panel dataset provides one of the most comprehensive pictures of US households available. The PSID started collecting information on a sample of roughly 5,000 households in 1968. Thereafter, both the original families and their split-offs (children of the original household forming households of their own) have been followed. The survey was annual until 1996 and became biennial starting in 1997. From 1999 to 2013, it introduced a fairly comprehensive measure of consumption that makes it possible to investigate how changes in households' income affects their consumption behavior.

In cleaning and preparing the data for estimation, I follow the approach laid out by Kaplan et al. (2014) and drop households with missing information on race, education, or state of residence as well as those whose income grows more than 500%, falls by more than 80%, or is below 100 dollars. I also drop households that have top-coded income or consumption and households that appear in the sample fewer than three consecutive times because identification of the coefficients of interest requires a minimum of three periods. Finally, I only keep households whose head is 25 to 62 years old. The final sample, then, has 25,871 observations between 1999 and 2011.

After the estimation is implemented using the PSID data, I impute the results into the observations of the ASEC supplement of the CPS, which is conducted every March. This supplement to the CPS has the longest and largest sample as well as the most comprehensive collection of data on labor force status, work experience, and different types of income. I expand the range of years in the analysis to include more data points. From 1990 to 2017, there are 1,370,477 household observations, with an average of about 50,000 observations per year; 1995 has the lowest number, 35,110, and 2002 the highest, 58,826.

1.3.2 Average MPC Results: National and State Levels

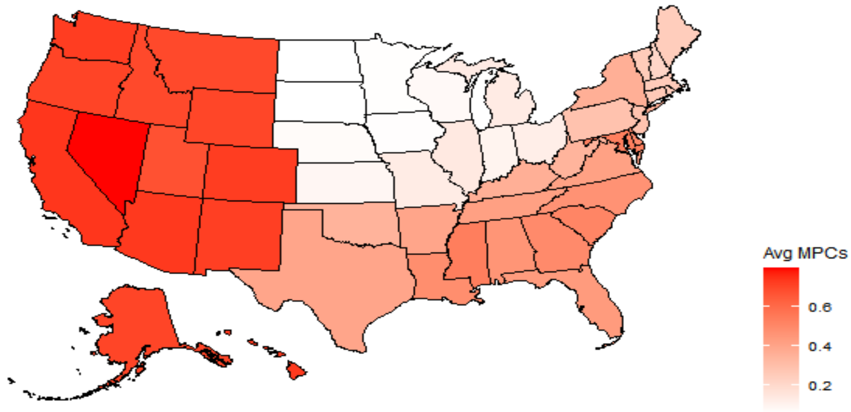
Before I discuss the state-level analysis, it is important to compare my national findings with the literature. Carroll et al. (2014) have provided a summarized table from the extensive review of Jappelli and Pistaferri (2010).[11] Despite striking differences in estimation methodology, country of focus, data analyzed, measures of consumption, and the transitory income shock studied, most estimates of aggregate MPC range between 0.2 and 0.6. Since the covariance term of aggregate MPC is relatively small, as I show later, the average MPC of 0.41 I find is right in the middle of that range. Moreover, it is almost the same value estimated by Patterson (2020), 0.42.

This result provides a firm foundation for the state-level estimates. To the best of my knowledge, this is the first study to estimate the average MPC of states within the United States. Even though the results should be interpreted with caution due to the small number of observations in some places, my final estimations show great heterogeneity among states. Household average MPCs range from 0.06 in North Dakota to 0.80 in Washington DC, with a standard deviation of 0.24 and a mean of 0.41. However, the great variability of estimates is a phenomenon mostly observed across regions, not within them. Figure 1.1 provides a visual representation of these findings. The average MPC estimated for the Midwest region is 0.09, the lowest in the country, and it is 0.72 for the West, by far the highest. The Northwest and the South are in the middle, with average MPC estimates of 0.27 and 0.47, respectively.

The great disparity between US states' average MPCs may raise concerns regarding the validity of the findings. The relatively small sample analyzed could, indeed, be affecting the size of the estimates, but the pattern of regional average MPC is consistent with the median household debt-to-income ratio for the US regions. For instance, in 2017, the last year of the estimated period, the median household debt-to-income ratios for the West, South, Northeast, and Midwest were 1.72, 1.38, 1.34,

[11]See also Fagereng et al. (2019), Gelman (2021), Gross et al. (2020), Jappelli and Pistaferri (2014), and Kaplan et al. (2014) for more recent estimations.

Figure 1.1: Income-weighted Average MPC by State



Note: Own estimation using PSID and ASEC-CPS data.

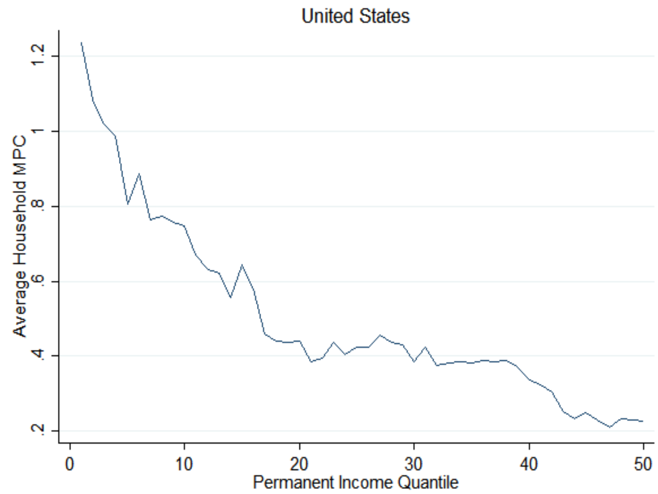
and 1.11, respectively. These results are in line with the findings of previous studies that estimate higher MPCs for liquidity-constrained households.

1.3.3 Average MPC and Income Inequality: An Empirical Analysis

1.3.3.1 Household MPC by Permanent Income

In section 1.2, I assert that aggregate MPC will only be affected by changes in income distribution if household MPCs are heterogeneous and associated with income level. I next investigate whether this relationship holds in the data. For each household in the sample, I measure its position in the distribution of permanent income and classify households into (50) quantiles. To construct the measure of permanent income, I run a Mincer-style regression. I regress log labor income on dummies for gender, race, marital status, education, age, and occupation, as well as interactions

Figure 1.2: Income-weighted Average Household MPC by Permanent Income Quantile



Note: PSID estimation supplemented by ASEC-CPS data.

between education and age and between gender and age, to capture some heterogeneity in life-cycle earnings profiles. I run the regressions at the national and state levels using ASEC-CPS data from 1990 to 2017.[12]

Concerning how household MPC relates to income level in the United States overall, figure 1.2 shows that the higher the permanent income quantile, the lower the consumption response is to a shock in earnings. No U-shape is found. Furthermore, other demographic patterns presented in the literature are also corroborated by my analysis. MPC for households whose head is black is greater than for those who head is white; female heads of household also present higher MPCs than males, and the MPC for age groups displays a J-shaped form.

[12]The use of a measure of permanent income for this analysis is justified by the work of DeBacker et al. (2013). They decompose the increase in income inequality into permanent and transitory components and find the vast majority of the increase in inequality is due to dispersion in the permanent component of income.

The same pattern found in the national analysis regarding the behavior of household MPC in each permanent income quantile is observed in every state. Appendix A provides a graphical visualization of this relationship for each state. These figures show that MPC is not linearly decreasing in income and that there are some major fluctuations in several states. However, it is clear that lower permanent income is associated with higher household MPC and that higher permanent income is associated with lower MPC.

1.3.3.2 Correlation between Income Inequality and Average MPC

I next examine how average state MPC relates to the state income inequality level. Since average MPC is estimated using a period of several years, in this case from 1990 to 2017, the choice of inequality measure for the analysis is not straightforward. Data from Dr. Mark W. Frank's website measuring state-level income inequality[13] from 1990 to 2015 show that, excluding Alaska, all states became more unequal. The Gini coefficient increased, on average, 7.6%, whereas the income share of the top 10% of the population increased 21.5% on average. Because I am interested in a cross-section analysis of how average MPC correlates with different levels of inequality, changes within states are not as important as changes between states.[14] In this regard, the coefficient of correlation between top 10% income shares of states in 1990 and 2015 is 0.84, indicating a persistence in state inequality ranking. On the other hand, for the Gini, this coefficient is only 0.44.[15]

[13] See M. Frank (2014) for the explanation of how these measures are constructed.

[14] Changes within a state are still an issue that should be considered. In section 1.5, the empirical investigation uses annual state-level inequality measures.

[15] If Alaska is excluded, the coefficient value jumps to 0.69.

I would argue, therefore, that the average income inequality level of each state between 1990 and 2015 is a reasonable measure to analyze the relationship between inequality and average MPC. There are obvious caveats, but this approach at least provides a direction for better understanding the effects of inequality on average household MPC. Table 1.1 presents the correlation between state income-weighted average MPC and five different measures of average state income inequality between 1990 and 2015: the income share of the top 10% of the population, the Gini coefficient, the Atkinson index, the relative mean deviation of income, and the Theil index. The results indicate that higher inequality is associated with higher MPC, even though it is a weak relationship.

This finding could indicate a polarization in the income distribution that favors more low-income/high-MPC households to the detriment of middle-income/low-MPC households, as theoretically demonstrated by Iyigun and Owen (2004). However, it could also be the case that some other factor increases income inequality while also decreasing average MPC. I return to this issue in section 1.5. Now, I move to the empirical estimation of the unequal incidence of shocks to investigate the other channel through which inequality might affect aggregate MPC.

Table 1.1: Correlation between State Income-Weighted Average MPC and Average Income Inequality Levels (1990–2015)

	Income-Weighted Average MPC
Top 10%	0.177
Gini Coefficient	0.351
Atkinson Index	0.181
Relative Mean Deviation	0.317
Theil Index	0.187

Note: State-level inequality measures are extracted from Dr. Mark W. Frank's website. State-level income-weighted average household MPC is estimated combining PSID and ASEC-CPS data.

1.3.3.3 Correlation between Income Inequality and Household MPC

To build my theoretical model, I assumed in section 1.2.1 that higher levels of income inequality are associated with a higher share of credit-constrained households in the region. An increase in the share of constrained households would then translate into relatively more high-MPC households in the economy. This important hypothesis can be tested by more closely analyzing the estimations of household MPCs given the position of the households in the permanent income distribution. If higher inequality leads to a higher share of constrained households, then I should observe higher levels of household MPC in the lowest permanent income quantiles in states with higher income inequality.

To investigate this assumption, I perform a simple correlation analysis between the average household MPC of each permanent income quantile and the average income inequality level of each state between 1990 and 2015. Table 1.2 exhibits the results of this analysis for the bottom five quantiles. As predicted, there is an expressive positive correlation between inequality and each income quantile at bottom of the distribution, except for the first quantile. This finding comes as no surprise since households in the bottom quantile are already subject to great constraints and usually live hand to mouth. When inequality increases and credit access becomes more difficult, households at the lower end of the income distribution suffer, but those at the extreme end are not affected that much.

1.4 Unequal Incidence of Shocks

In estimating the covariance between household MPCs and the sensitivities of household incomes to aggregate movements, I follow the method proposed by Alves et al. (2020). This method provides a link to the income inequality question I am

Table 1.2: Correlation between Income Quantile Average Household MPC and Average Income Inequality Levels (1990–2015)

	Permanent Income Quantile				
	1st	2nd	3rd	4th	5th
Top 10%	0.135	0.420	0.314	0.463	0.352
Gini Coefficient	0.212	0.433	0.370	0.531	0.447
Atkinson Index	-0.036	0.363	0.317	0.470	0.400
Relative Mean Deviation	0.118	0.436	0.393	0.556	0.471
Theil Index	-0.041	0.353	0.295	0.455	0.383

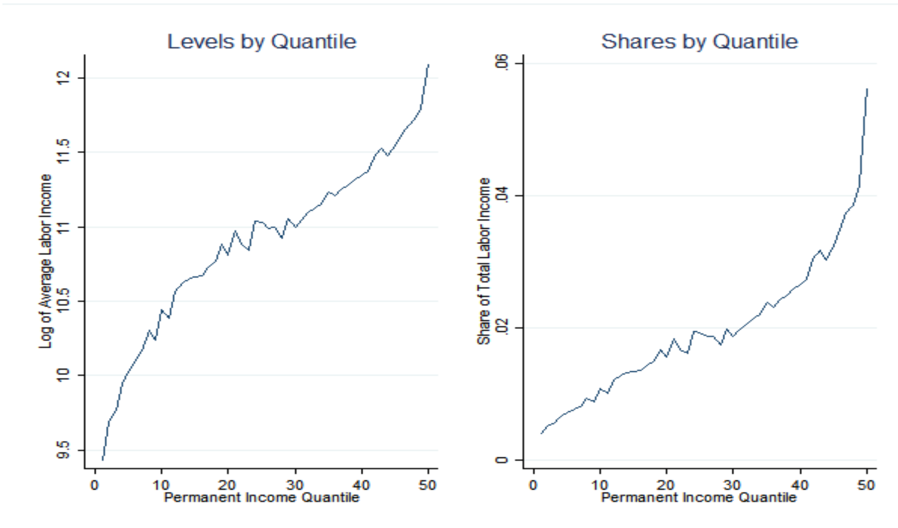
Note: State-level inequality measures are extracted from Dr. Mark W. Frank's website. State-level income-weighted average household MPC is estimated combining PSID and ASEC-CPS data.

trying to answer. They formalize the incidence function and allocate individuals to specific groups associated with several fixed characteristics (which they call types z) because it is not feasible to estimate the degree of exposure for each individual.[16] Then, to implement the empirical analysis, they summarize all these characteristics (such as gender, education, age, and occupation) into a single variable, the permanent component of labor income. Likewise, for each household in the sample, I use the same method implemented in the previous section to measure its position in the distribution of permanent income and categorize households into (50) quantiles. Next, I estimate the income shares and the elasticities for each quantile.

I analyze household dynamics instead of individuals, and my time horizon is shorter than the one Alves et al. (2020) use. Consequently, figure 1.3 reports the log of average labor income (left panel) and the share of total income (right panel) by quantiles of permanent income z for the United States for 2015 so I can compare my findings with the results in Alves et al. (2020). Even if the magnitudes are not the

[16] See Alves et al. (2020) for details.

Figure 1.3: Log-level and Shares of Labor Income by Permanent Income Quantile in 2015 (United States)



same, the patterns are very similar. Average labor income increases in permanent income, and the shares also rise, with a spike in the top quantiles.

The next step is to estimate the elasticities along the entire distribution of permanent income. Let y_{it}^z be the labor income of household i, belonging to quantile z of permanent income in year t. Elasticities $\gamma(z)$ are then estimated using the following (constrained) system of equations:[17]

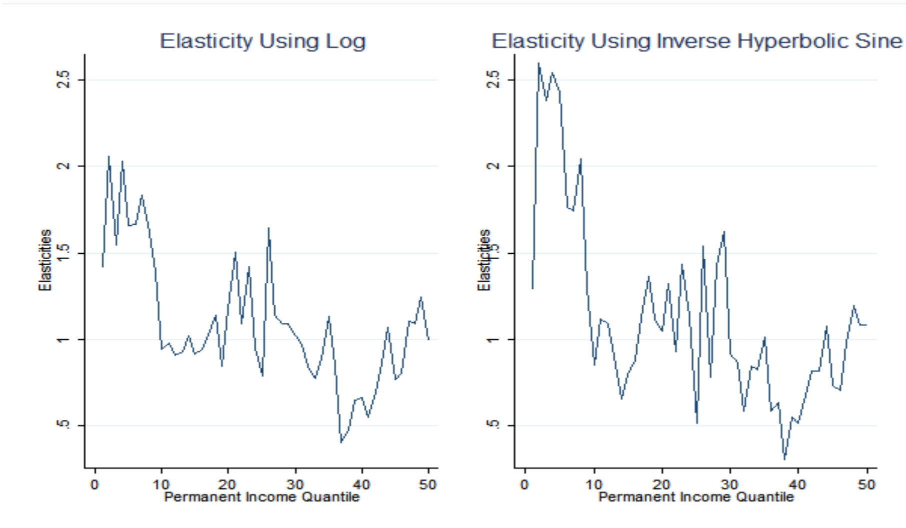
$$\begin{aligned} logy_{i,t}^z = \beta_0(z) + \beta_1(z)t + \gamma(z)logY_t + \varepsilon_{i,t}, \forall z \in \{1, ..., 50\} \\ s.t. \sum_{z=1}^{50} \overline{s}(z)\gamma(z) = 1, \end{aligned} \tag{1.8}$$

where Y_t is aggregate income and $\overline{s}(z)$ is the average income share of quantile z.

Finally, Alves et al. (2020) provide a simple solution to retain zero income observations, which are frequent in the data and are dropped when using log earnings. As is commonly used in statistics, they replace the log operator in equation (1.5)

[17] See Alves et al. (2020) for theoretical justification to impose this constraint.

Figure 1.4: Elasticity of Permanent Income Quantile Using Different Specifications



with the inverse hyperbolic sine (asinh):

$$asinh(y) = log(y + \sqrt{y^2 + 1}). \tag{1.9}$$

This approach addresses the possible negative bias in $\gamma(z)$ due to the greater likelihood that zero incomes will occur when aggregate earnings are low, especially at the low end of the income distribution.

1.4.1 US National Covariance and Aggregate MPC

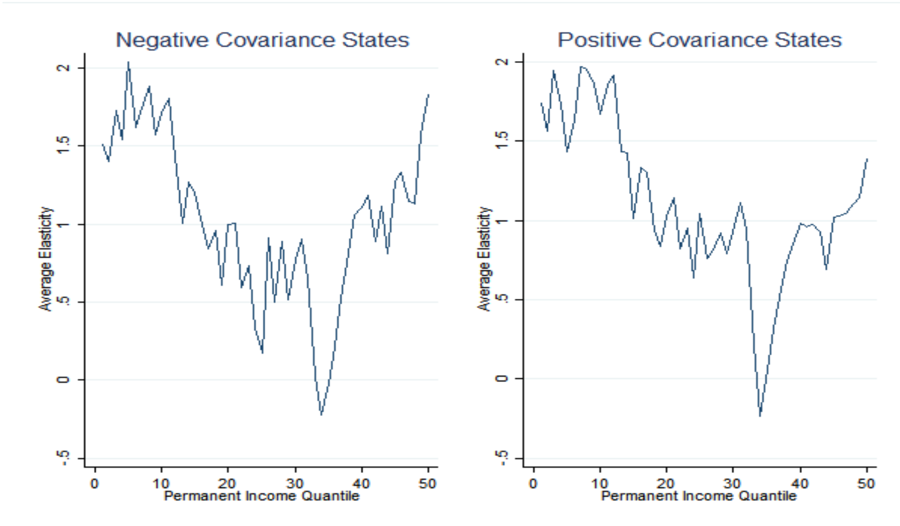
The results of elasticities and covariance estimations are in line with findings in both Patterson (2020) and Alves et al. (2020). Figure 1.4 shows the elasticity of each quantile of permanent income, with regular log earnings on the left panel and the inverse hyperbolic sine approach on the right. As expected, the bottom of the distribution presents more exposure to the cycles using the alternative strategy. Nevertheless, the pattern of higher elasticity for the lower income quantiles is the same.

This elasticity distribution, associated with household MPCs, yields a positive covariance. It must be remembered that this amplification mechanism for shocks is the exact result anticipated since households that are more exposed to fluctuations in aggregate income are also those with higher MPCs. The covariances of 0.03 (log income) and 0.04 (asinh) are lower than the 0.06 estimated by Patterson (2020), likely because my analysis covers households, whereas she investigates individuals. Households should be less vulnerable to shocks due to the possibility of income smoothing through household formation. Moreover, the difference between the aggregate MPC when there is equal incidence of shocks (covariance is equal to 0) and when shock incidence is unequal is an increase of 6.5% in the case of log income elasticity and 9.7% when using the inverse hyperbolic sine approach. These variations are much lower than the 28% increase found by Patterson (2020) in the estimation of individual aggregate MPC.

1.4.2 US State-Level Covariance and Aggregate MPC

When I shift the analysis to states, the results become even more interesting. Some states present positive covariances, although others yield negative ones. These results mean that, even though at the national level the unequal incidence of shocks translates into an amplification mechanism, at the state level, some locations similarly experience the amplification of shocks, but others experience dampening. I have already shown that all states exhibit the same pattern of low (high) income/high (low) household MPC. Hence, the difference in the sign of the covariance must come from differences in the elasticities. Figure 1.5 shows exactly this pattern. The left panel displays the average elasticity of each permanent income quantile in states with negative covariance. The right panel shows the elasticities of states with posi-

Figure 1.5: Average Elasticity of Permanent Income Quantile at the State Level



tive covariance. Even though in both sets of states elasticity is high in the bottom 10 quantiles, for states with negative covariance, elasticity is also high at the extremes of the income distribution. Negative covariance states also exhibit lower elasticities for middle-income households. Since the covariance term is income-weighted, and high-income households have a higher income share, the effect of their exposure to fluctuations in aggregate income given their low MPCs outweighs the effect of lower-income households.

The mean covariances of all states are smaller than those at the national level, 0.01 (log income) and 0.03 (asinh). However, the range of estimates is from -0.06 to 0.07 in the case of log income and -0.12 to 0.22 in the case of the inverse hyperbolic sine. Nevertheless, the calculated aggregate MPCs have a distribution similar to that of the average MPCs. The estimates range from 0.07 (log income) and 0.06 (asinh) in North Dakota to 0.84 (log income) and 0.93 (asinh) in Nevada, with standard deviations of 0.24 (log income) and 0.25 (asinh) to the means of 0.42 (log income) and 0.44 (asinh).

The next question is how the covariances, and finally the aggregate MPCs, relate to income inequality. When inequality increases, the mechanism that reflects households' exposure to shocks is accentuated. Therefore, if covariance is positive, greater inequality causes the covariance to rise, increasing amplification. If, on the other hand, covariance is negative, then covariance decreases with more inequality, increasing dampening. Table 1.3 presents the correlation between state income-weighted covariance and the average state income inequality level between 1990 and 2015. The first and most important result is that covariance is positively correlated with income inequality when covariance is positive and negatively correlated when covariance is negative. However, when covariance is positive, this correlation is very low, while it is higher (in absolute terms) when covariance is negative. One possible explanation for this phenomenon is the fact that in states with positive covariance, high-MPC households have higher elasticities and low-MPC households have low elasticities. Thus, a redistribution of income will not affect the structure of the income-weighted covariance. On the other hand, in states with negative covariance, both low- and high-MPC households exhibit high elasticities. Therefore, when income is redistributed to the top income earners, the covariance term becomes more negative.

Here I investigate how this translates into the relationship between aggregate MPC and inequality. When every state is considered, higher income inequality is correlated with higher aggregate MPC. As expected, this relationship becomes stronger when only states with positive covariance are considered. In contrast, when covariance is negative, the correlation is mixed depending on the inequality measure used.

These results indicate that a rise in income inequality may be converted into a rise in aggregate MPC primarily through an increase in average MPC. When covariance

Table 1.3: Correlation between State Income-Weighted Covariance and Average Income Inequality Level (1990–2015)

	Positive Covariance		Negative Covariance	
	log	asinh	log	asinh
Top 10%	0.100	0.194	-0.294	-0.310
Gini Coefficient	0.068	0.180	-0.157	0.026
Atkinson Index	0.022	0.106	-0.208	-0.379
Relative Mean Deviation	0.085	0.162	-0.204	-0.273
Theil Index	0.001	0.112	-0.180	-0.341

Note: State-level inequality measures are extracted from Dr. Mark W. Frank's website.

is positive, this is amplified. When covariance is negative, it is diminished, but it is unclear whether this decrease is enough to offset or even exceed the change in average MPC. In the next section, I therefore implement an empirical investigation to try to establish causation regarding this effect and better understand the dynamics of the covariance.

1.5 Effect of Inequality on Consumption Volatility: Empirical Investigation

Up to this point, I have been able to establish a correlation between aggregate MPC and income inequality, even though the relationship does not seem to be strong. Theoretically, based on the discussion in section 1.2, one could argue that the correlations observed in the data arise from the fact that changes in the income distribution affect aggregate MPC. However, other factors may simultaneously influence both variables. For instance, most studies examining the effects of inequality on economic volatility identify the share of credit-constrained households as the channel through which the relationship is manifested. The higher the relative number of households that cannot smooth their consumption, the higher the MPC and consumption volatility will be.[18] I showed that this mechanism might be driven by the increase in income inequality levels itself. However, if at the same time a high inequality of credit availability yields more income concentration at the top of the distribution, then the correlation between inequality and aggregate MPC may also be driven by these dynamics.

With this in mind, to test the hypothesis that changes in income inequality affect aggregate consumption through changes in aggregate MPC due to the direct mechanisms discussed in earlier sections, I must control for the effects of credit availability. Not only that, but I must establish a strategy that connects all these variables in a consistent way. I assume that state-level consumption is affected by changes in national-level GDP but that changes in consumption in individual states may not necessarily move national GDP. I therefore regress changes in each US state aggregate consumption against an inequality measure interacting with changes in US output.[19] The goal is to capture how income inequality affects consumption volatility given shocks in the economy.

For this, I use data from all 50 US states plus the District of Columbia to estimate a panel data model from 1998 to 2015.[20] Annual state-level aggregate data come from the Bureau of Economic Analysis (BEA): Regional Economic Accounts. Annual national GDP also comes from the BEA, while demographic controls are extracted from the ASEC dataset. I use the same inequality measures as in my

[18]See Iyigun and Owen (2004) for a deeper discussion of these associations.

[19]This is a similar approach to the one used by Patterson (2020) when she investigates the amplification of shocks at the commuting zone level.

[20]The time period is limited by state-level aggregate data availability.

previous analyses, from Dr. Mark W. Frank's website. From this, I estimate the following equation:

$$\Delta logC_{t,s} = \phi_1 Ineq_{t-1,s} \times \Delta logG_t + X'\Phi + \delta_s + \delta_t + \varepsilon_{t,s} \tag{1.10}$$

where $\Delta logC_{t,s}$ is the change in log aggregate consumption of state s between periods t and $t-1$, $Ineq_{t-1,s}$ is the income inequality level in state s in $t-1$, $\Delta logG_t$ is the change in log national GDP between periods t and $t-1$, X is a vector of demographic and credit availability controls, and δ_s and δ_t are state- and time-fixed effects, respectively. Demographic controls include the average age and lagged earnings of the area as well as the fraction of the state population that is female, black, and in the labor force in $t-1$, each included separately and interacted with $\Delta logG_t$. Credit availability controls include state output shares of the finance and insurance industry and the real estate, rental, and leasing industry, included independently and interacted with $\Delta logG_t$.

Table 1.4 shows the results for regressions using both the income share of the top 10% of the population and the Gini coefficient as measures of inequality considering all states. Table 1.5 analyzes only states with positive covariance, and table 1.6 shows results only for states with negative covariance. The estimated coefficients are exactly as predicted and indicate that there might be a positive causal relationship between income inequality and aggregate consumption volatility through aggregate MPC.

Overall, when there is a shock in aggregate GDP, higher inequality is associated with larger swings in consumption. As expected, this effect is stronger when covariance acts as an amplification mechanism and is weaker when covariance dampens the effect of the shock. Quantitatively, the consumption response to changes in inequality is very low. However, everything else constant, a one-percentage-point shock to aggregate GDP will have, on average, double the impact on aggregate consumption if the state inequality level measured as the income share of the top 10% of the population is the maximum observed in the sample, 0.622, compared to the minimum one, 0.329.

1.6 Conclusion

Economists and policymakers continue to debate how rising income inequality affects the economy. Many predict that more inequality leads to negative economic outcomes. I advanced the understanding of this topic by investigating the relationship between income inequality and aggregate consumption volatility. By introducing a comprehensive analysis of how increasing income inequality affects aggregate consumption volatility through changes in average and aggregate household MPC, this paper provides a path forward in the discussion.

Consumption volatility has a significant welfare cost. Therefore, understanding the mechanisms that affect the variability of consumption can help inform policies designed to reduce aggregate fluctuations. Thus, to increase their reliability and produce more accurate outcomes, monetary policy models may need to incorporate the interactions between income inequality and household consumption responses to income shocks.

If changes in inequality levels are indeed associated with the response of aggregate household consumption to a shock, then the economies in US states with different levels of income inequality might respond differently to a national monetary policy. Therefore, it is imperative to study the effectiveness of monetary policy given the different levels of income inequality across states.

Moreover, the analysis presented in this paper can be extended to investigate how more inequality might affect output and unemployment fluctuations. Finally, given the findings about the covariance term signal varying across states, it is compelling to more deeply study this phenomenon to understand the underlying dynamics causing it.

Table 1.4: Effect of Income Inequality Level on Aggregate Consumption Sensitivity to Aggregate Shocks–Overall

	(1)	(2)	(3)
Inequality Measure: Top 10% Share			
$Ineq_{t-1,s} \times \Delta logG_t$	3.618***	4.021***	3.789***
	(0.921)	(0.875)	(0.817)
Inequality Measure: Gini Coefficient			
$Ineq_{t-1,s} \times \Delta logG_t$	3.116***	2.819***	2.858***
	(0.729)	(0.724)	(0.548)
Year FE	X	X	X
State FE	X	X	X
Demographic Controls		X	X
Credit Controls			X
No. Observations	918	918	918
R-Squared	0.806	0.819	0.835

Note: In all columns, the dependent variable is the change in log aggregate consumption at the state level. Demographic controls include the average age and lagged earnings of the area as well as the fraction of the state population that is female, black, and in the labor force in $t-1$, each included separately and interacted with $\Delta logG_t$. Credit availability controls include state output share of the finance and insurance industry and the real estate, rental, and leasing industry, included independently and interacted with $\Delta logG_t$. Standard errors in parentheses are clustered at the state level. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 1.5: Effect of Income Inequality Level on Aggregate Consumption Sensitivity to Aggregate Shocks–Positive Covariance

	(1)	(2)	(3)
Inequality Measure: Top 10% Share			
$Ineq_{t-1,s} \times \Delta logG_t$	4.689***	5.223***	4.672***
	(1.381)	(1.096))	(1.047)
Inequality Measure: Gini Coefficient			
$Ineq_{t-1,s} \times \Delta logG_t$	3.671***	3.012***	3.027***
	(0.966)	(0.985)	(0.620)
Year FE	X	X	X
State FE	X	X	X
Demographic Controls		X	X
Credit Controls			X
No. Observations	612	612	612
R-Squared	0.790	0.808	0.834

Note: In all columns, the dependent variable is the change in log aggregate consumption at the state level. Demographic controls include the average age and lagged earnings of the area as well as the fraction of the state population that is female, black, and in the labor force in $t-1$, each included separately and interacted with $\Delta logG_t$. Credit availability controls include state output share of the finance and insurance industry and the real estate, rental, and leasing industry, included independently and interacted with $\Delta logG_t$. Standard errors in parentheses are clustered at the state level. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

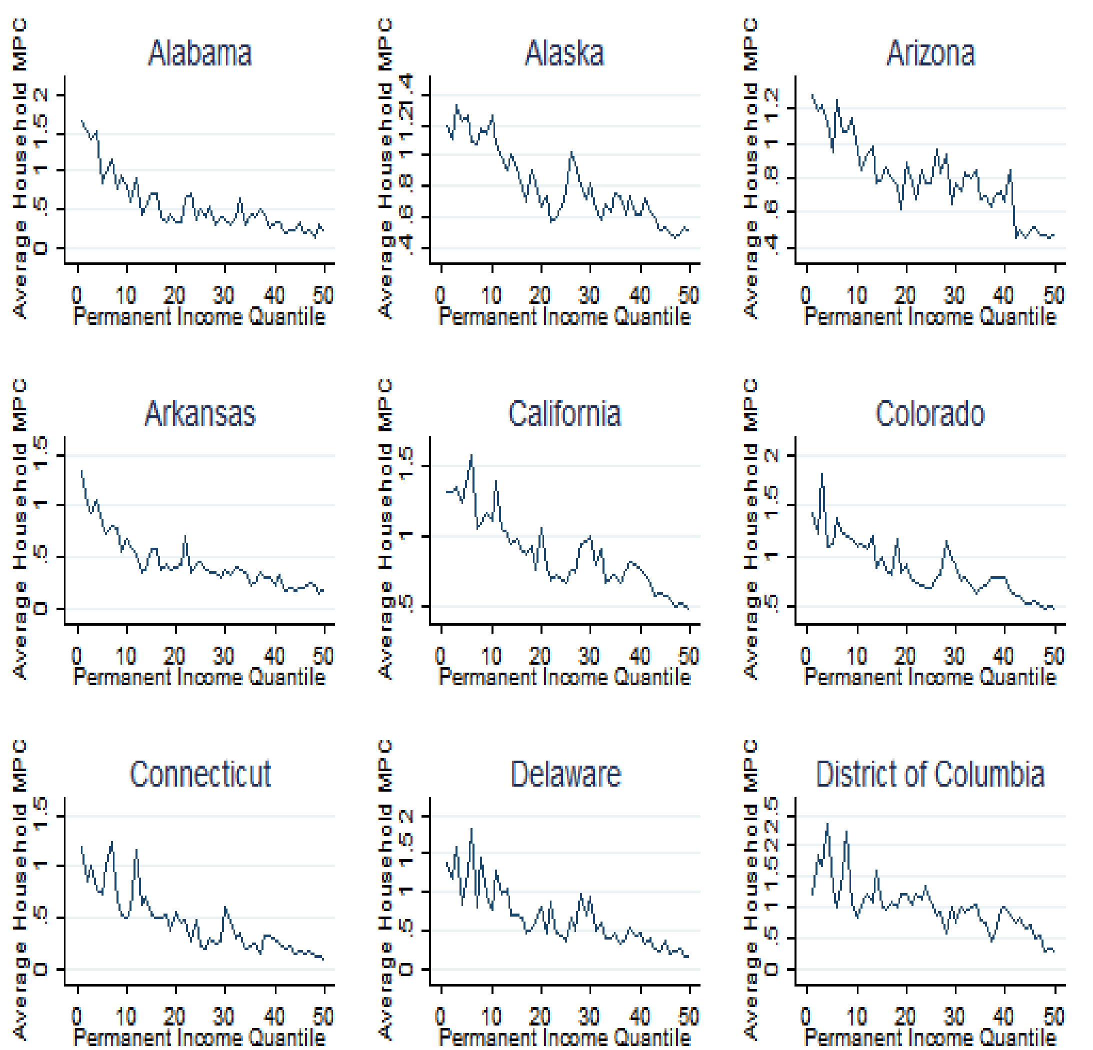
Table 1.6: Effect of Income Inequality Level on Aggregate Consumption Sensitivity to Aggregate Shocks–Negative Covariance

	(1)	(2)	(3)
Inequality Measure: Top 10% Share			
$Ineq_{t-1,s} \times \Delta logG_t$	1.887**	2.322***	2.385***
	(0.872)	(0.789)	(0.755)
Inequality Measure: Gini Coefficient			
$Ineq_{t-1,s} \times \Delta logG_t$	1.945*	1.779	1.688
	(1.144)	(1.187)	(1.197)
Year FE	X	X	X
State FE	X	X	X
Demographic Controls		X	X
Credit Controls			X
No. Observations	306	306	306
R-Squared	0.853	0.866	0.868

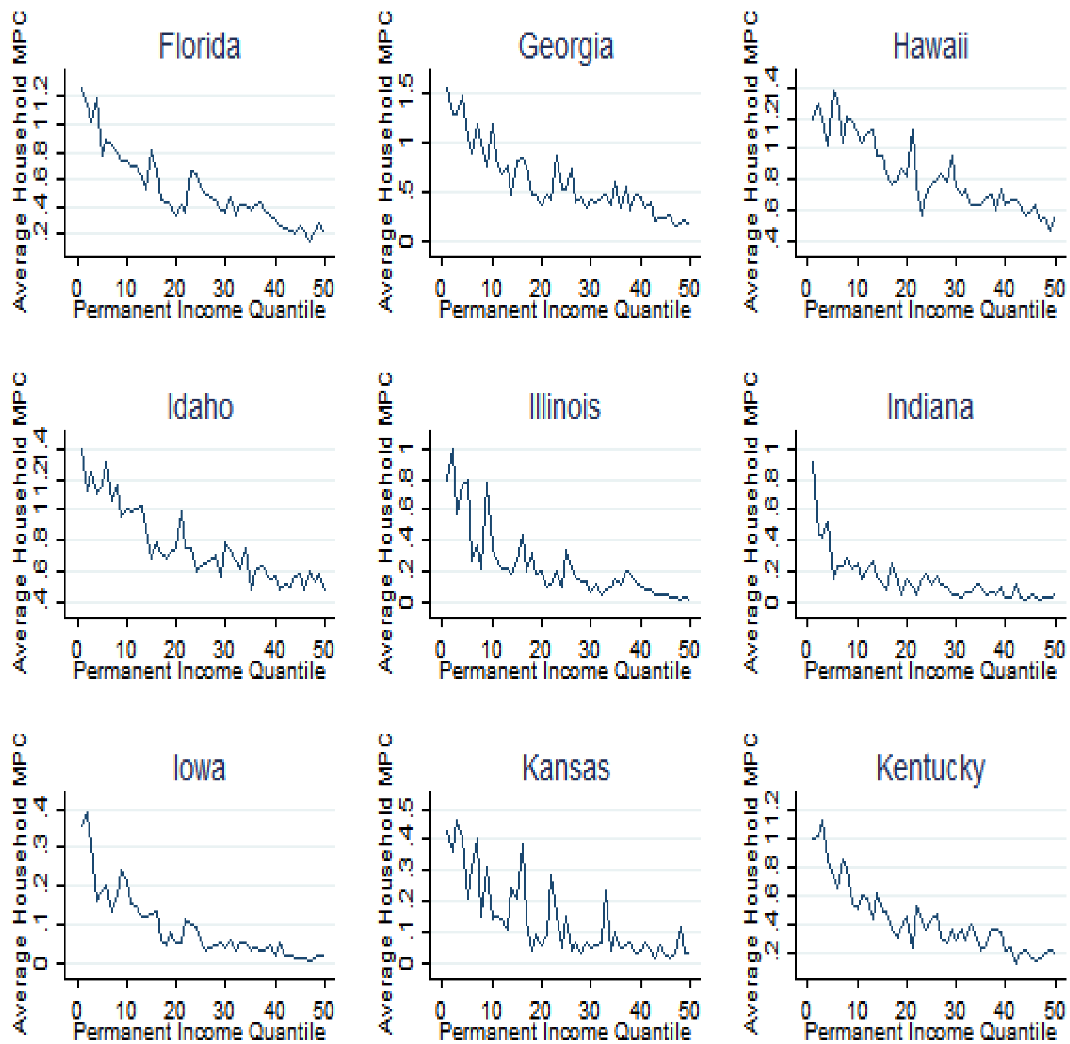
Note: In all columns, the dependent variable is the change in log aggregate consumption at the state level. Demographic controls include the average age and lagged earnings of the area as well as the fraction of the state population that is female, black, and in the labor force in $t-1$, each included separately and interacted with $\Delta logG_t$. Credit availability controls include state output share of the finance and insurance industry and the real estate, rental, and leasing industry, included independently and interacted with $\Delta logG_t$. Standard errors in parentheses are clustered at the state level. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

1.7 Appendix A: State-Level Income-Weighted Average MPC by Permanent Income Quantile

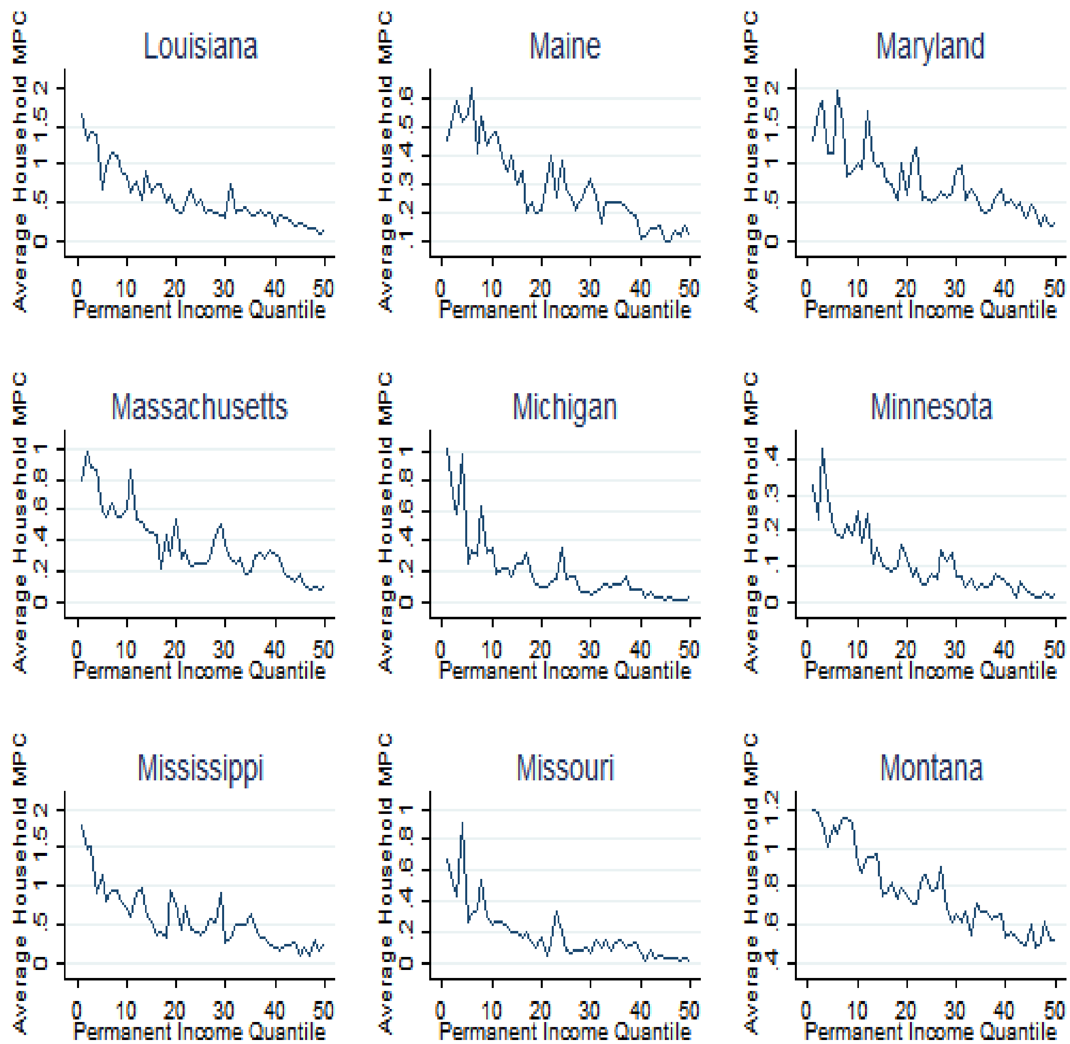
Figure 1.6: State-Level Income-Weighted Average MPC by Permanent Income Quantile



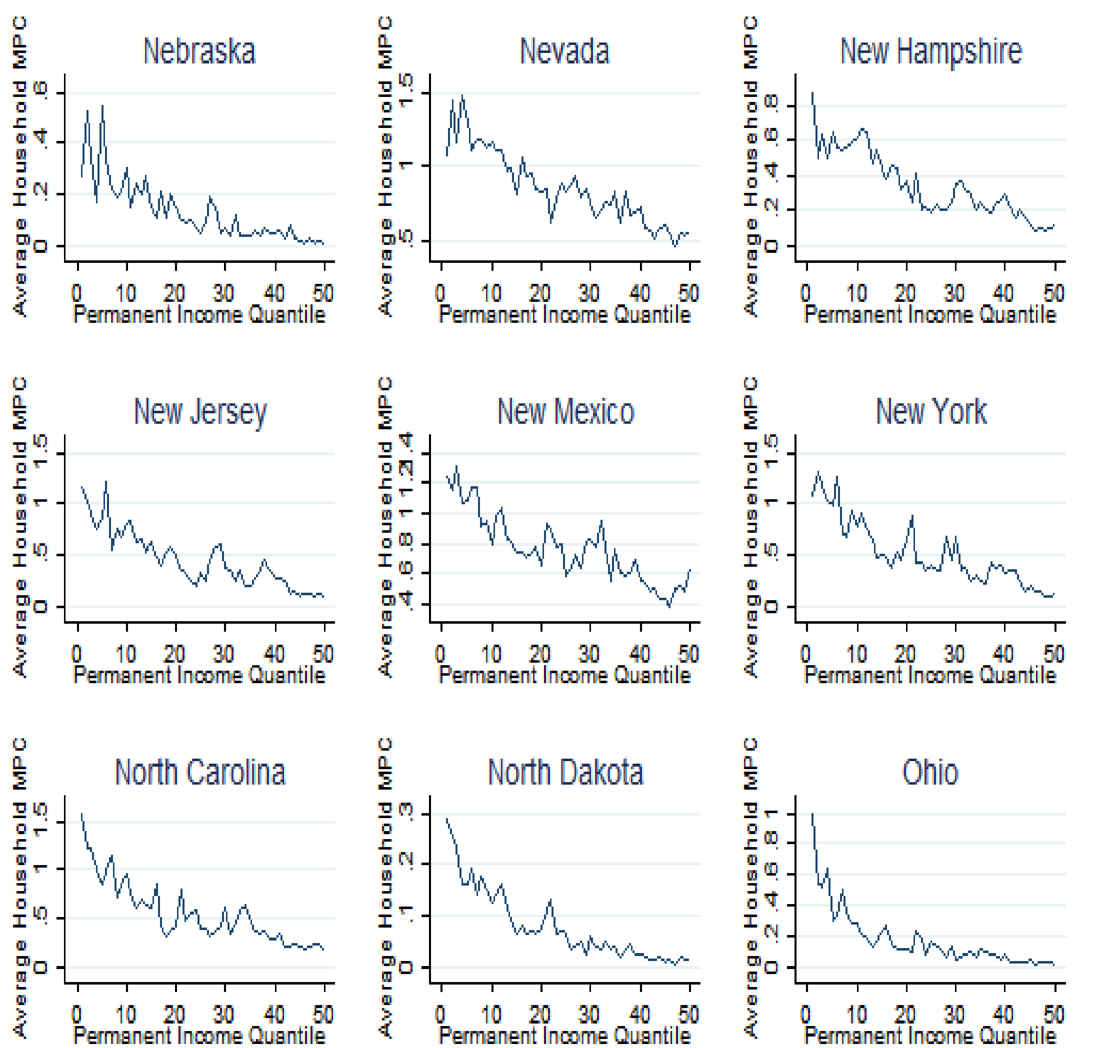
State-Level Income-Weighted Average MPC by Permanent Income Quantile–Continuation



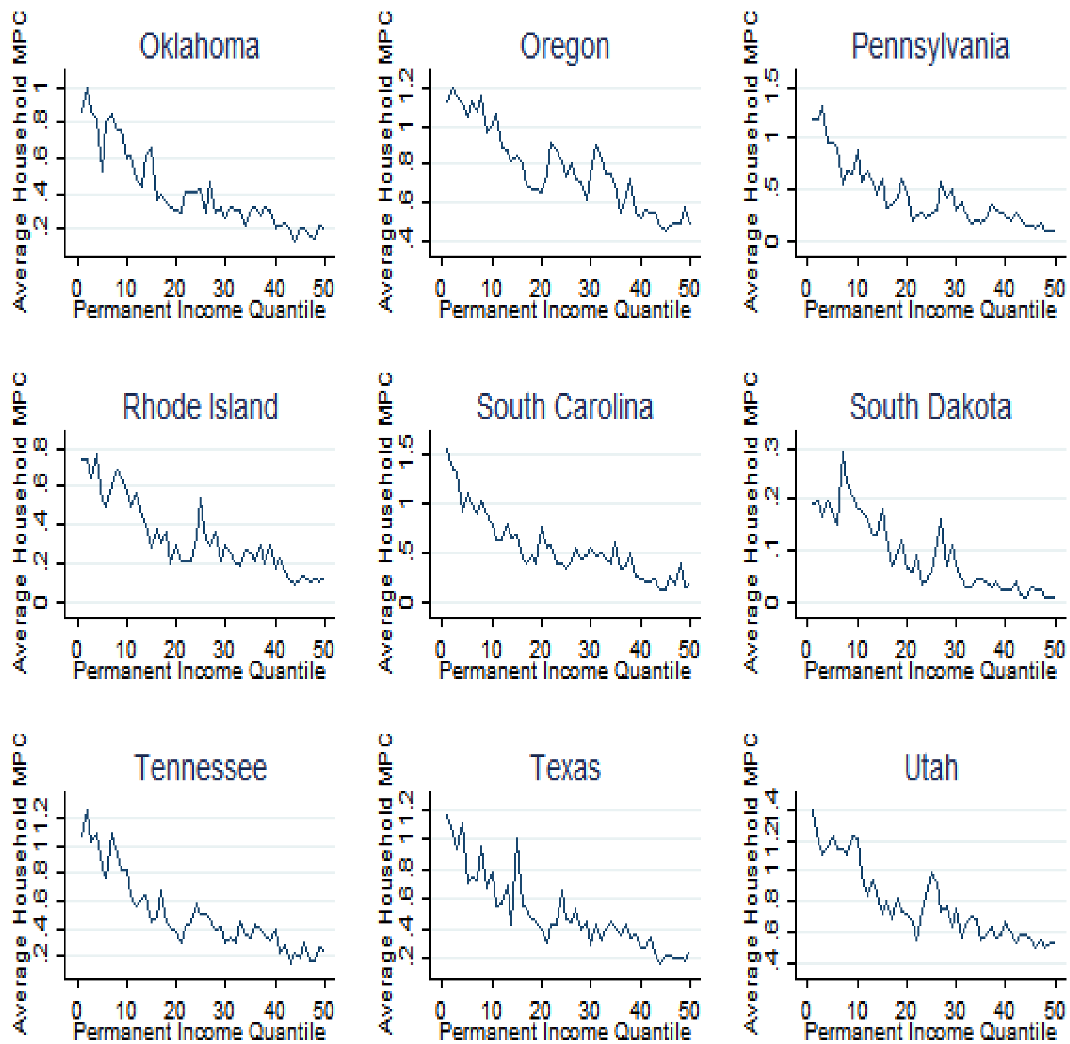
State-Level Income-Weighted Average MPC by Permanent Income Quantile–Continuation



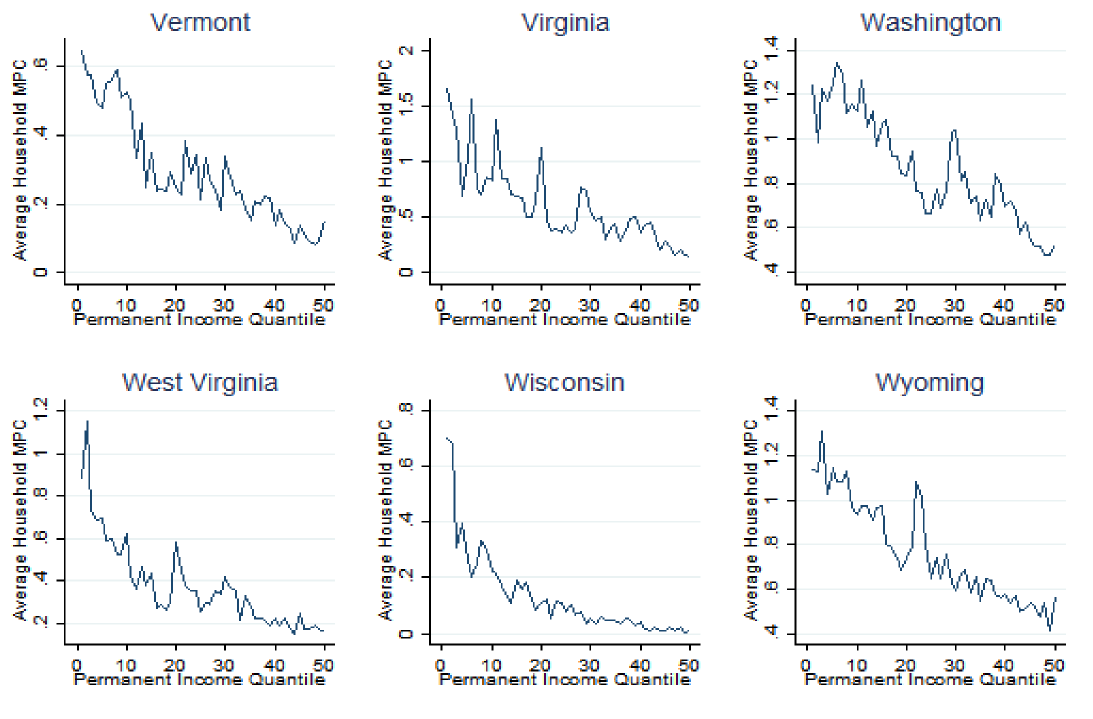
State-Level Income-Weighted Average MPC by Permanent Income Quantile–Continuation



State-Level Income-Weighted Average MPC by Permanent Income Quantile–Continuation



State-Level Income-Weighted Average MPC by Permanent Income Quantile–Continuation



CHAPTER 2

INCOME INEQUALITY AND HOUSE PRICES: EVIDENCE FROM US COUNTIES

2.1 Introduction

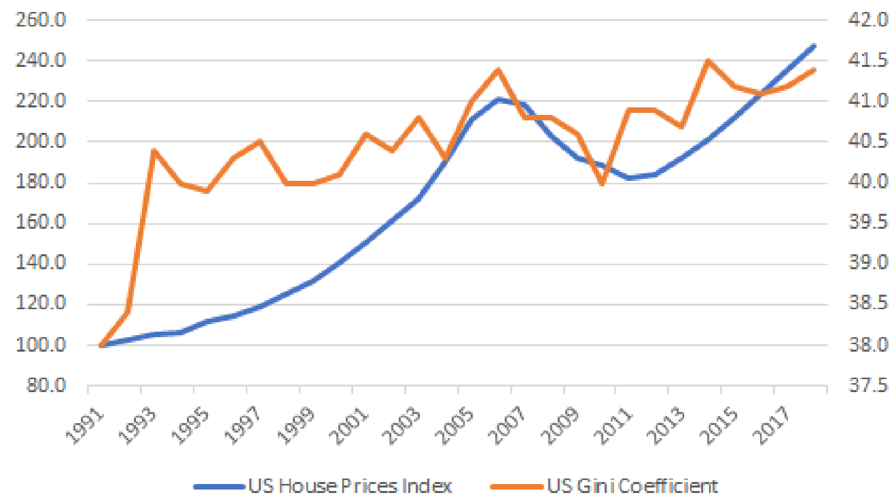
Over the past three decades, income inequality in the United States, measured by the Gini coefficient, has increased by 9.2%, from 0.38 to 0.415.[1] In the same period, house prices across the country also rose sharply, even considering the boom-bust cycle in between. The national house price index calculated by the US Federal Housing Finance Agency shows an astounding increase of 147% in the average price of houses. Figure 2.1 illustrates this phenomenon. The question posed is whether the increasing gap in the income distribution contributed to higher house prices in the United States.

This work is not the first to ask this question, but it is the first to use a panel of annual US county-level data to answer it. I find that, in fact, higher inequality is associated with higher house prices overall. A 1% increase in the Gini coefficient means a 0.04% increase in the average price of all houses measured by the Zillow index between 2007 and 2015. This result holds when I use the price of different segments separately. For example, a 1% rise in the Gini coefficient is associated with an approximately 0.03% rise in the average price of both bottom- and top-tier houses.

When I consider a model specification including an interaction term between the Gini coefficient and mortgage interest rates, I find that what is driving housing

[1] According to data from the World Bank, from 1991 to 2018. It should be noted that other measures also show a sharp increase in income inequality in the United States. For example, the income share of the top 10% of the population increased by 19.6%, from 38.3% to 45.8%, according to the World Inequality Database.

Figure 2.1: House Prices and Income Inequality in the United States



Note: The left axis measures the house prices index, and the right axis measures the Gini coefficient. Income inequality data comes from the World Bank, and the house prices index is calculated by the US Federal Housing Finance Agency.

prices up following an increase in income inequality is an interest rates channel. The effect for the isolated Gini coefficient becomes negative for a measure of the prices of all houses and also when considering only the top-tier or bottom-tier houses. However, the coefficient for the interaction between inequality and interest rates is positive and dictates the overall effect in every housing segment.

Intuitively, these results might be explained by the fact that an increase in income inequality leads to a rise in housing demand at the top of the income distribution and at the same time may drive demand down at the bottom. The effect on overall prices is ambiguous. However, if we assume that households at the top are lenders and low- and middle-income households are borrowers, higher interest rates will lead to a higher transfer of income from the bottom to the top, which can lead to a dominant effect of the increase in demand of high-income households, causing average housing prices to go up.

These findings have many policy implications because changes in house prices can have important macro- and microeconomic effects. For example, rising house prices may have wealth and collateral effects. It can stimulate consumer spending and economic growth when it increases homeowners' sense of security and facilitates access to credit (Case et al., 2005; Campbell & Cocco, 2007). Furthermore, a sharp rise in prices can make housing unaffordable, which significantly affects low-income families, especially in the most productive urban areas (Dewilde & Lancee, 2013; DeFusco et al., 2018). Finally, house price inflation can translate into retail price inflation (Vavra et al., 2014), which can have important implications for monetary policy.

This chapter's main contributions are the use of very disaggregated data to analyze the effect of rising income inequality on housing prices and the proposal of a new interest rate channel that plays an important role in this relationship. The panel estimation using annual US county-level data provides a more robust analysis than more aggregated measures. It not only has more observations from which to extract information but also allows for an examination of local market dynamics, which might differ considerably from state- and national-level overall patterns. This work, therefore, advances both the specific literature that investigates the relationship between income inequality and housing prices and also the broader literature interested in understanding the economic effects of changes in inequality. As I find a positive and significant effect of widening income distribution on the prices of houses, I also contribute to the literature that examines the determinants of housing prices changes.

Other empirical papers have also found that rising income inequality leads to higher housing prices. Goda et al. (2020), for example, claim that income inequality has driven up house prices in most OECD countries between 1975 and 2010. They argue that this relationship is driven by an increase in the total demand for houses when inequality is higher. Using household survey data, Zhang (2015) and Zhang et al. (2016) investigated the housing market in China. The former found that higher income inequality within cities is significantly correlated with a higher housing cost burden. The latter has shown that the Gini coefficient has a positive relationship with the housing price-to-income ratio and the housing vacancy rate.

Considering the effects of rising income inequality on housing costs, Matlack and Vigdor (2008) investigated housing markets in American metropolitan areas between 1970 and 2000. They found that higher inequality is associated with significantly higher rents per room and greater crowding among households headed by a high-school dropout in markets with low-vacancy rates. Furthermore, Fligstein et al. (2017) have analyzed the period of the housing market bubble prior to the Great Recession of 2008–2009 and show that in areas where income inequality was higher, all movers went deeper into debt and increased their monthly housing costs to live in more desirable neighborhoods.

Nonetheless, there are also papers that find a negative relationship between income inequality and housing prices. For instance, Määttänen and Terviö (2014) have argued that, theoretically, the impact of increased income inequality on house prices depends on the shapes of the distributions. Empirically investigating the relationship, they suggested that higher income inequality between 1998 and 2007 had a negative impact on average house prices in six US metropolitan areas. Moreover, Hailemariam et al. (2021) analyzed a panel of 17 OECD countries over more than a century. They also found that an increase in income inequality has a significant negative effect on real house prices. Finally, using a panel of US states, Kösem (2021) has theoretically and empirically shown that following a rise in inequality, house prices and mortgage debt decline, whereas aggregate default risk increases.

Considering these contradicting findings in prior research, my goal is to provide more reliable evidence of the effects of rising income inequality on house prices. The remainder of this chapter is organized as follows: Section 2.2 provides an overview of the possible channels through which inequality affects housing prices. Section 2.3 describes the empirical strategy and the data used in the analysis. Section 2.4 discusses the empirical results. Finally, section 2.5 presents a conclusion.

2.2 How Income Inequality Affects Housing Prices

Hailemariam et al. (2021) provide a list of reasons covered in the literature for why an increase in income inequality might, both direct and indirectly, cause housing prices to move. They indicate that a rise in income inequality is initially associated with higher housing prices through an increase in demand for houses at the top of the income distribution alongside a limited supply of housing stock (Määttänen & Terviö, 2014; DeFusco et al., 2018). As housing prices rise, low-income households are forced out of the market. Furthermore, as a direct result of the bidding process, which boosts the value of houses, homeowners and investors expect house prices to continue to rise and will hold on to properties that would otherwise be put on the market, further limiting supply and pushing prices up.

Another channel through which rising income inequality might lead to higher housing prices is socioeconomic sorting (Lupton & Power, 2004). If high-income households own the houses in more desirable areas while less-desirable neighborhoods are concentrated in the hands of low-income households, an increase in income inequality will lead to a sharp rise in the prices of houses in the desirable locations. This price increase spills over the rest of the market, increasing the overall average price of houses.

This price contagion could be caused by a “keeping up with the Joneses” scenario. As the high-income households expand their housing consumption and bid up prices for houses in the most desirable areas, those with income right below feel compelled to keep up by buying less expensive houses but at a higher price (R. H. Frank, 2007). This competition spreads through the housing market, forcing lower-income households to take on greater housing expenditures or forego buying a house altogether.

There are also many channels that could work for a negative effect of higher income inequality on housing prices. Since high levels of income disparity are generally accompanied by lower social trust, lower social mobility, and higher crime rates, these undesirable characteristics could cause housing prices to decrease (Lynch & Rasmussen, 2001; Tita et al., 2006).

Furthermore, housing prices might be negatively affected by a borrower risk composition channel of income inequality. In an analytical general equilibrium model, Kösem (2021) shows that an exogenous mean-preserving rise in income inequality increases the share of households that opt for mortgages with default risk and this depresses housing demand and prices. This result is achieved because when inequality is high, the marginal risk-taking borrower is at the top of the income distribution. Therefore, households in the middle of the income distribution switch from risk-free mortgages to risky mortgages, while those at the bottom or top do not change their expected default risk. Furthermore, as low-income households with risky loans have a high loan-to-income ratio, when they have a low share of total income, the total demand for mortgages is also low. Hence, a rise in income inequality increases risk-taking and decreases house prices.

With so many explanations with contradicting results present in the literature, in the next subsection, I propose a new and simple theoretical interpretation of the effect that rising income inequality has on housing prices considering an interest rate channel. Later in this chapter, I test this theory with US county-level data.

2.2.1 Simple Theoretical Framework

An easy way to demonstrate how increasing income inequality can lead to higher housing prices is using the illustration proposed by Matlack and Vigdor (2008). Assuming that households are either low-income or high-income, I can draw demand and supply curves for housing, as shown in figure 2.2.[2] In Panel A, the housing demand of high-income households shifts to the right as their income grows alongside an increase in income inequality. In Panel B, housing demand of low-income households does not change if I assume that rising inequality is driven by higher income at the top of the income distribution. Therefore, in Panel C, there is a shift in the market demand for housing that drives prices up.[3]

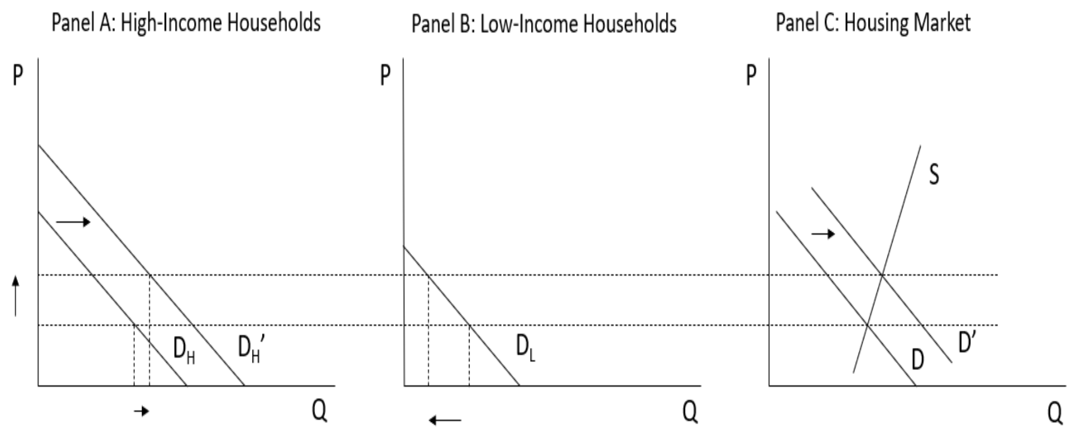
Building from the analysis in Matlack and Vigdor (2008), I assume that instead of two, there are three types of households in the economy: low-income, middle-income, and high-income. In this case, only the middle- and high-income households participate in the housing market. Moreover, low- and middle-income are borrowers, and high-income households are lenders. Hence, a higher interest rate benefits those in the top of the income distribution.

Now we should consider an increase in income inequality characterized by a decrease in the share of middle-income households and an increase in the proportion

[2]I also assume that housing is a normal good and that housing supply is inelastic to some degree.

[3]This effect on prices could be diminished or even reversed if higher income inequality was also characterized by lower income in the bottom of the distribution. Moreover, allowing for production differentiation or household heterogeneity in the housing market could also lead to ambiguous results.

Figure 2.2: Partial Equilibrium Housing Market Model (Matlack & Vigdor, 2008)

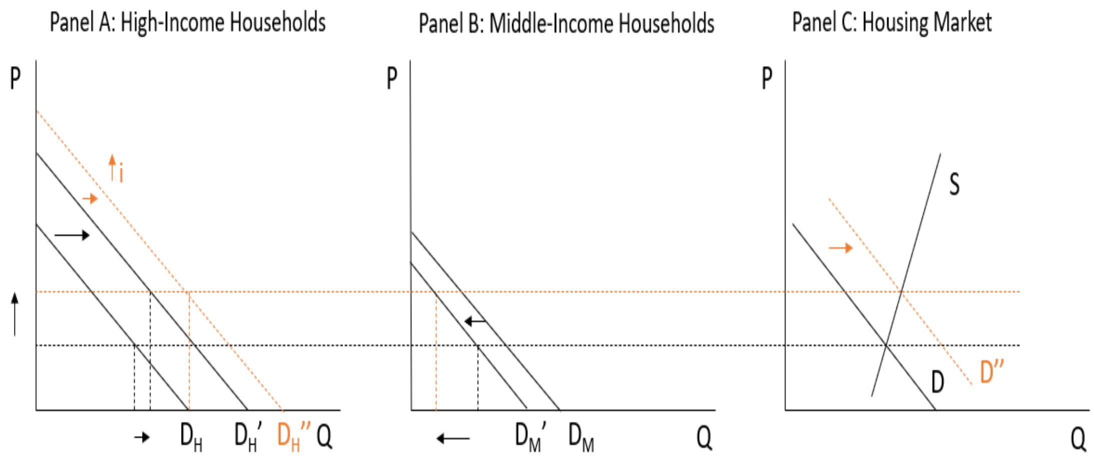


of households at the tails of the income distribution. In this scenario, shown in figure 2.3, housing demand of high-income households increases (Panel A), and housing demand of middle-income households decreases (Panel B). The effect on the market demand is ambiguous since it depends on the dynamics of households' socioeconomic mobility. However, since high-income households are lenders, and the others are borrowers, this characterization of inequality increase will lead to a higher share of income moving to the top of distribution as interest rates increase. Therefore, the higher the level of interest rates, the greater the chance of an increase in income inequality leading to a larger market demand for houses and, consequently, higher housing prices.

2.3 Empirical Strategy

One of the contributions of this work is to investigate how rising income inequality affects housing prices using a panel of US counties in the period from 2007 to 2015. Many other papers have used both US state-level and metropolitan-level annual

Figure 2.3: Partial Equilibrium Housing Market Model with Lenders and Borrowers



data to investigate the relationship between inequality and housing prices. Not many have also used cross-section county-level data. However, to my knowledge, this is the first one to use annual county-level data in this analysis.

2.3.1 Model Specification

The empirical strategy relies on two simple panel specifications. The baseline equation is the following:

$$logHP_{i,t} = logGini_{i,t-1} + X_{i,t} + Z_{i,t-1} + \delta_i + \gamma_t + u_{i,t} \tag{2.1}$$

where $logHP_{i,t}$ is the log of a housing price measure for county i in year t; $logGini_{i,t-1}$ is the log of the Gini coefficient measure for county i in the previous year; $X_{i,t}$ is a set of county and state control variables in year t, which includes county population, state GDP growth, and state effective mortgage rate; $Z_{i,t-1}$ is a set of county control variables in year $t-1$, which includes the mean debt-to-income ratio of households in the county, the median applicant income in the county, and the median family income in the closest metropolitan area; δ_i are time-fixed effects; γ_t are county-fixed effects; and $u_{i,t}$ is an error term. The Gini coefficient and some of the control variables are lagged in the estimated equation because there might be a feedback effect from house prices to them.

After I estimate equation (2.1), I add an interaction term between the log of the Gini coefficient and the effective mortgage rate to investigate the interest rate channel through which rising income inequality might affect housing prices.

$$logHP_{i,t} = logGini_{i,t-1} + logGini_{i,t-1} * IntRate_{i,t} + X_{i,t} + Z_{i,t-1} + \delta_i + \gamma_t + u_{i,t} \quad (2.2)$$

Equation (2.2) only adds the interaction term $logGini_{i,t-1} * IntRate_{i,t}$ to equation (2.1).

2.3.2 Data

The greatest challenge to implement an annual panel analysis of county-level income inequality is to find a reliable measure for it. Thus, I use the data from Jha et al. (2019), who constructed Gini coefficients for the majority of US counties from 2005 to 2015 using publicly available household data provided by the Internal Revenue Service (IRS). First, they gathered annual zip-code level data on adjusted gross income from the Statistics of Income collected by the IRS.[4] Then they combined the areas considering population weights to construct the Gini coefficient for each county. County population data also come from Jha et al. (2019).

Housing price data come from Zillow Home Value Index (ZHVI), a monthly, smoothed, seasonally adjusted measure of the typical home value and market changes

[4]These data can be downloaded from https://www.nber.org/data/soi-tax-stats-individual-income-tax-statistics-zip-code-data-soi.html.

across a given region and housing type. It reflects the typical value for homes in the 35th to 65th percentile range. Since the data is at a monthly frequency, I calculate the average value for the year. I also use other measures published by Zillow to investigate the effect of rising income inequality on different types of housing. I use both the top-tier ZHVI, which measures the typical value for homes within the 65th to 95th percentile range for a given region, and bottom-tier ZHVI, which measures the typical value for homes that fall within the fifth to 35th percentile range. Moreover, I use the ZHVI for all single-family residences, for condo/co-ops, and for all homes with one, two, three, four, and 5+ bedrooms.

State GDP growth data is estimated by the US Bureau of Economic Analysis. For effective mortgage rate, I use data from the Federal Housing Finance Agency's Monthly Interest Rate Survey. It provides state-level monthly data, which I use to calculate an annual average. I assume that every county within a state implements the same mortgage rate.

All other variables come from the Home Mortgage Disclosure Act (HMDA) collected by the Consumer Financial Protection Bureau for mortgages applications across the United States between 2007 and 2015. I use the microdata to calculate both the median applicant income and mean debt-to-income ratio for each county every year. Median family income is provided in the files.

2.4 Empirical Results

Table 2.1 shows the results for the estimations of equations (2.1) and (2.2) using prices for all houses, while table 2.2 displays the results for only top-tier houses and table 2.3 the estimates for only the bottom tier. The baseline model indicates that a 1% increase in the Gini coefficient is associated with a 0.036% increase in the average price of all houses, a significant but not quantitatively impressive result. The positive relationship between income inequality and housing prices holds also for both bottom- and top-tier houses. The fact that a 1% increase in the Gini coefficient raises the value of both measures by approximately 0.03% might indicate a spillover effect from higher-valued houses to lower-valued ones.

When I consider the effect of an interaction between income inequality and interest rates, the coefficients change considerably, but the overall effect of inequality on housing prices remains practically the same. Examining all houses, the isolated effect of a 1% increase in the Gini coefficient on housing prices becomes negative. However, the higher the interest rate, the greater is the increase in prices when inequality rises. In a county with low interest rates, the overall effect would be negative. Since the mean rate across counties over time is 4.83%, the interaction between income inequality and interest rates leads to an increase in housing prices when inequality rises. This result is in line with the simple theoretical framework proposed in section 2.2.2.

As the share of middle-income households decreases, there is a downward pressure over market demand. Since part of the middle-income households turns into high income, there is also a competing upward pressure on market demand for housing. If interest rates are too low, the income increase at the top does not compensate the loss of income at the bottom, and housing prices decrease. If interest rates are high enough, the income at the top of the distribution will rise enough to increase market demand for housing and prices.

To investigate if the results hold for different periods and are not skewed by the Great Recession of 2008–2009, I estimate equations (2.1) and (2.2) only for the period between 2010 and 2015. Tables 2.4, 2.5, and 2.6 show the results. The relationship between income inequality and housing prices is still positive, and stronger.

In the baseline specification, a 1% increase in the Gini coefficient is associated with a 0.157% increase in prices. That is 4.4 times higher than before. When I consider the interaction between inequality and interest rates, interestingly the isolated Gini effect becomes positive. In this case, the main channel driving prices up when inequality increases is not through interest rates. The prices for bottom- and top-tier houses experience the same changes. The only difference is that now increasing inequality is associated with a much higher increase in the prices at the top.

2.5 Conclusion

There is still much of debate among economists regarding the effects that rising income inequality have on housing prices. There is no definite theoretical answer; hence, empirical investigation is key to understanding the true nature of this relationship. In this chapter, I used annual US county-level data for the first time in the literature. This strategy provides a more thorough analysis of the impacts on housing markets than works that rely on more aggregated data. The effects that manifest in smaller markets could be diluted when we consider bigger areas.

Moreover, I proposed a new theoretical framework that can help in understanding the channels through which higher income inequality might affect housing prices. Moving forward, the interest rate channel I highlight should be considered not only in empirical investigations but also in theoretical models that incorporate income inequality and house prices. My simple specification only accounts for partial equilibrium; thus, an expansion to a general equilibrium scheme is welcomed.

It is also interesting to expand this analysis to the renting market, especially because it affects predominantly low- and middle-income households. Furthermore, with more disaggregated data, it is possible to investigate the roles that regional socioeconomic and demographic characteristics play in the relationship between income inequality and housing prices.

Table 2.1: Effect of Changes in Income Inequality on All House Prices (2007–2015)

	(1)	(2)
$logGini_{t-1,s}$	0.036***	-0.069**
	(0.007)	(0.029)
$logGini_{t-1,s} \times MortgageRate_{t,s}$		0.024***
		(0.006)
Contemporary Controls	X	X
Lagged Controls	X	X
Year FE	X	X
County FE	X	X
No. of Observations	17,132	17,132
No. of Counties	2,482	2,482
R-Squared	0.99	0.99

Note: In all columns, the dependent variable is the log of the Zillow Home Value Index of the typical value for homes in the 35th to 65th percentile range. Contemporary controls include county population, state GDP growth, and state effective mortgage rate. Lagged controls include the mean debt-to-income ratio of households in the county, the median applicant income in the county, and the median family income in the closest metropolitan area. Standard errors in parentheses are clustered at the county level. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 2.2: Effect of Changes in Income Inequality on Top-Tier House Prices (2007–2015)

	(1)	(2)
$logGini_{t-1,s}$	.033***	-0.059**
	(0.007)	(0.027)
$logGini_{t-1,s} \times MortgageRate_{t,s}$		0.021***
		(0.006)
Contemporary Controls	X	X
Lagged Controls	X	X
Year FE	X	X
County FE	X	X
No. of Observations	17,141	17,141
No. of Counties	2,483	2,483
R-Squared	0.99	0.99

Note: In all columns, the dependent variable is the log of the Zillow Home Value Index of the typical value for homes in the 65th to 95th percentile range. Contemporary controls include county population, state GDP growth, and state effective mortgage rate. Lagged controls include the mean debt-to-income ratio of households in the county, the median applicant income in the county, and the median family income in the closest metropolitan area. Standard errors in parentheses are clustered at the county level. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 2.3: Effect of Changes in Income Inequality on Bottom-Tier House Prices (2007–2015)

	(1)	(2)
$logGini_{t-1,s}$	0.031***	-0.107***
	(0.008)	(0.033)
$logGini_{t-1,s} \times MortgageRate_{t,s}$		0.032***
		(0.007)
Contemporary Controls	X	X
Lagged Controls	X	X
Year FE	X	X
County FE	X	X
No. of Observations	17,115	17,115
No. of Counties	2,482	2,482
R-Squared	0.99	0.99

Note: In all columns, the dependent variable is the log of the Zillow Home Value Index of the typical value for homes in the 5th to 35th percentile range. Contemporary controls include county population, state GDP growth, and state effective mortgage rate. Lagged controls include the mean debt-to-income ratio of households in the county, the median applicant income in the county, and the median family income in the closest metropolitan area. Standard errors in parentheses are clustered at the county level. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 2.4: Effect of Changes in Income Inequality on All House Prices (2010–2015)

	(1)	(2)
$logGini_{t-1,s}$	0.157***	0.077**
	(0.025)	(0.032)
$logGini_{t-1,s} \times MortgageRate_{t,s}$		0.019***
		(0.005)
Contemporary Controls	X	X
Lagged Controls	X	X
Year FE	X	X
County FE	X	X
No. of Observations	13,826	13,826
No. of Counties	2,482	2,482
R-Squared	0.99	0.99

Note: In all columns, the dependent variable is the log of the Zillow Home Value Index of the typical value for homes in the 35th to 65th percentile range. Contemporary controls include county population, state GDP growth, and state effective mortgage rate. Lagged controls include the mean debt-to-income ratio of households in the county, the median applicant income in the county, and the median family income in the closest metropolitan area. Standard errors in parentheses are clustered at the county level. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 2.5: Effect of Changes in Income Inequality on Top-Tier House Prices (2010–2015)

	(1)	(2)
$logGini_{t-1,s}$	0.155***	0.084***
	(0.023)	(0.029)
$logGini_{t-1,s} \times MortgageRate_{t,s}$		0.017***
		(0.005)
Contemporary Controls	X	X
Lagged Controls	X	X
Year FE	X	X
County FE	X	X
No. of Observations	13,829	13,829
No. of Counties	2,483	2,483
R-Squared	0.99	0.99

Note: In all columns, the dependent variable is the log of the Zillow Home Value Index of the typical value for homes in the 65th to 95th percentile range. Contemporary controls include county population, state GDP growth, and state effective mortgage rate. Lagged controls include the mean debt-to-income ratio of households in the county, the median applicant income in the county, and the median family income in the closest metropolitan area. Standard errors in parentheses are clustered at the county level. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 2.6: Effect of Changes in Income Inequality on Bottom-Tier House Prices (2010–2015)

	(1)	(2)
$logGini_{t-1,s}$	0.148***	0.052
	(0.026)	(0.035)
$logGini_{t-1,s} \times MortgageRate_{t,s}$		0.023***
		(0.005)
Contemporary Controls	X	X
Lagged Controls	X	X
Year FE	X	X
County FE	X	X
No. of Observations	13,822	13,822
No. of Counties	2,482	2,482
R-Squared	0.99	0.99

Note: In all columns, the dependent variable is the log of the Zillow Home Value Index of the typical value for homes in the 5th to 35th percentile range. Contemporary controls include county population, state GDP growth, and state effective mortgage rate. Lagged controls include the mean debt-to-income ratio of households in the county, the median applicant income in the county, and the median family income in the closest metropolitan area. Standard errors in parentheses are clustered at the county level. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

2.6 Appendix A: Summary Statistics

Table 2.7: Summary Statistics of Selected Variables (2007–2015)

	No. of Obs.	Mean	Std. Dev.	Min	Max
ZHVI All Houses	19,213	146,283.90	96,871.44	22,358.42	1,257,388.00
ZHVI Top Tier	19,229	250,210.60	189,474.90	46,419.83	4,511,756.00
ZHVI Bottom Tier	19,187	89,989.32	66,621.55	10,187.25	805,104.30
ZHVI 1-Bedroom	17,170	96,230.87	67,854.71	11,551.08	818,350.60
ZHVI 2-Bedroom	19,030	107,402.70	80,536.38	12,877.67	1,663,181.00
ZHVI 3-Bedroom	19,198	146,264.80	101,774.50	23,673.33	3,062,981.00
ZHVI 4-Bedroom	19,127	199,475.60	158,027.70	25,312.00	6,075,920.00
ZHVI 5-Bedroom	18,728	263,095.30	271,712.40	26,238.00	9,299,280.00
ZHVI Condo	11,884	153,219.40	78,452.15	23,585.67	1,194,293.00
ZHVI Single-family	19,213	149,201.70	114,070.10	22,358.42	2,524,153.00

Note: All variables are county-specific except for median family income, which is a metro area measure, as well as effective mortgage rate and GDP growth, which are state measures.

Summary Statistics of Selected Variables (2007–2015)–Continuation

	No. of Obs.	Mean	Std. Dev.	Min	Max
Gini	27,276	0.41	0.12	0.07	0.81
Median Family Income	28,933	55,309.92	11,894.33	15,400.00	121,600.00
Median Applicant Income	28,933	61,107.18	16,646.61	16,000	316,000.00
Mean Debt-to-Income Ratio	28,933	1.99	0.63	0.07	53.71
Effective Mortgage Rate	28,231	4.83%	0.92%	3.56%	6.71%
GDP Growth	28,231	1.32%	2.66%	-9.00%	22.40%
Population	28,197	99,372.71	317,222.70	61	10,100,000

Note: All variables are county-specific except for median family income, which is a metro area measure, as well as effective mortgage rate and GDP growth, which are state measures.

Table 2.8: Summary Statistics of Selected Variables (2010–2015)

	No. of Obs.	Mean	Std. Dev.	Min	Max
ZHVI All Houses	14,356	139,564.80	90,422.15	22,358.42	1,257,388.00
ZHVI Top Tier	14,359	238,877.70	177,686.40	46,419.83	4,511,756.00
ZHVI Bottom Tier	14,352	85,439.58	61,968.57	10,567.67	805,104.30
ZHVI 1-Bedroom	12,876	90,463.68	62,120.27	11,551.08	814,488.30
ZHVI 2-Bedroom	14,248	101,604.90	74,360.19	14,422.33	1,663,181.00
ZHVI 3-Bedroom	14,338	140,091.40	95,525.08	23,673.33	3,062,981.00
ZHVI 4-Bedroom	14,283	191,284.20	154,657.60	25,312.00	6,075,920.00
ZHVI 5-Bedroom	13,991	251,315.30	265,497.60	27,503.33	9,299,280.00
ZHVI Condo	8,755	146,175.20	73,029.20	23,585.67	1,194,293.00
ZHVI Single-family	14,356	142,251.30	107,657.90	22,358.42	2,524,153.00
Gini	18,162	0.37	0.09	0.07	0.77
Median Family Income	19,284	56,664.87	11,965.21	16,300.00	121,600.00
Median Applicant Income	19,284	62,477.36	16,906.62	16,000.00	298,500.00
Mean Debt-to-Income Ratio	19,284	1.99	0.67	0.07	53.71
Effective Mortgage Rate	18,816	4.28%	0.41%	3.56%	5.13%
GDP Growth	18,816	2.06%	2.11%	-5.00%	22.40%
Population	18,788	100,603.70	321,475.10	81	10,100,000

Note: All variables are county-specific except for median family income, which is a metro area measure, as well as effective mortgage rate and GDP growth, which are state measures.

2.7 Appendix B: Effect of Income Inequality on House Prices by Size and Type

Table 2.9: Effect of Changes in Income Inequality on One-Bedroom House Prices (2007–2015)

	(1)	(2)
$logGini_{t-1,s}$	0.010	-0.222***
	(0.012)	(0.051)
$logGini_{t-1,s} \times MortgageRate_{t,s}$		0.053***
		(0.010)
Contemporary Controls	X	X
Lagged Controls	X	X
Year FE	X	X
County FE	X	X
No. of Observations	15,269	15,269
No. of Counties	2,240	2,240
R-Squared	0.98	0.98

Note: In all columns, the dependent variable is the log of the Zillow Home Value Index of the typical value for 1-bedroom homes in the county. Contemporary controls include county population, state GDP growth, and state effective mortgage rate. Lagged controls include the mean debt-to-income ratio of households in the county, the median applicant income in the county, and the median family income in the closest metropolitan area. Standard errors in parentheses are clustered at the county level. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 2.10: Effect of Changes in Income Inequality on Two-Bedroom House Prices (2007–2015)

	(1)	(2)
$logGini_{t-1,s}$	0.032***	-0.104***
	(0.009)	(0.037)
$logGini_{t-1,s} \times MortgageRate_{t,s}$		0.031***
		(0.008)
Contemporary Controls	X	X
Lagged Controls	X	X
Year FE	X	X
County FE	X	X
No. of Observations	16,976	16,976
No. of Counties	2,467	2,467
R-Squared	0.99	0.99

Note: In all columns, the dependent variable is the log of the Zillow Home Value Index of the typical value for 2-bedroom homes in the county. Contemporary controls include county population, state GDP growth, and state effective mortgage rate. Lagged controls include the mean debt-to-income ratio of households in the county, the median applicant income in the county, and the median family income in the closest metropolitan area. Standard errors in parentheses are clustered at the county level. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 2.11: Effect of Changes in Income Inequality on Three-Bedroom House Prices (2007–2015)

	(1)	(2)
$logGini_{t-1,s}$	0.029***	-0.086***
	(0.007)	(0.029)
$logGini_{t-1,s} \times MortgageRate_{t,s}$		0.027***
		(0.006)
Contemporary Controls	X	X
Lagged Controls	X	X
Year FE	X	X
County FE	X	X
No. of Observations	17,115	17,115
No. of Counties	2,480	2,480
R-Squared	0.99	0.99

Note: In all columns, the dependent variable is the log of the Zillow Home Value Index of the typical value for 3-bedroom homes in the county. Contemporary controls include county population, state GDP growth, and state effective mortgage rate. Lagged controls include the mean debt-to-income ratio of households in the county, the median applicant income in the county, and the median family income in the closest metropolitan area. Standard errors in parentheses are clustered at the county level. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 2.12: Effect of Changes in Income Inequality on Four-Bedroom House Prices (2007–2015)

	(1)	(2)
$logGini_{t-1,s}$	0.032***	-0.031
	(0.007)	(0.032)
$logGini_{t-1,s} \times MortgageRate_{t,s}$		0.015**
		(0.007)
Contemporary Controls	X	X
Lagged Controls	X	X
Year FE	X	X
County FE	X	X
No. of Observations	17,045	17,045
No. of Counties	2,405	2,405
R-Squared	0.99	0.99

Note: In all columns, the dependent variable is the log of the Zillow Home Value Index of the typical value for 4-bedroom homes in the county. Contemporary controls include county population, state GDP growth, and state effective mortgage rate. Lagged controls include the mean debt-to-income ratio of households in the county, the median applicant income in the county, and the median family income in the closest metropolitan area. Standard errors in parentheses are clustered at the county level. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 2.13: Effect of Changes in Income Inequality on Five-Bedroom House Prices (2007–2015)

	(1)	(2)
$logGini_{t-1,s}$	0.032***	-0.39
	(0.009)	(0.034)
$logGini_{t-1,s} \times MortgageRate_{t,s}$		0.016**
		(0.007)
Contemporary Controls	X	X
Lagged Controls	X	X
Year FE	X	X
County FE	X	X
No. of Observations	16,680	16,680
No. of Counties	2,427	2,427
R-Squared	0.99	0.99

Note: In all columns, the dependent variable is the log of the Zillow Home Value Index of the typical value for 5-bedroom homes in the county. Contemporary controls include county population, state GDP growth, and state effective mortgage rate. Lagged controls include the mean debt-to-income ratio of households in the county, the median applicant income in the county, and the median family income in the closest metropolitan area. Standard errors in parentheses are clustered at the county level. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 2.14: Effect of Changes in Income Inequality on Condo Prices (2007–2015)

	(1)	(2)
$logGini_{t-1,s}$	0.045***	-0.085
	(0.015)	(0.056)
$logGini_{t-1,s} \times MortgageRate_{t,s}$		0.029**
		(0.012)
Contemporary Controls	X	X
Lagged Controls	X	X
Year FE	X	X
County FE	X	X
No. of Observations	10,292	10,292
No. of Counties	1,487	1,487
R-Squared	0.98	0.98

Note: In all columns, the dependent variable is the log of the Zillow Home Value Index of the typical value for condos in the county. Contemporary controls include county population, state GDP growth, and state effective mortgage rate. Lagged controls include the mean debt-to-income ratio of households in the county, the median applicant income in the county, and the median family income in the closest metropolitan area. Standard errors in parentheses are clustered at the county level. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 2.15: Effect of Changes in Income Inequality on Single-Family House Prices (2007–2015)

	(1)	(2)
$logGini_{t-1,s}$	0.036***	-0.066**
	(0.007)	(0.028)
$logGini_{t-1,s} \times MortgageRate_{t,s}$		0.024***
		(0.006)
Contemporary Controls	X	X
Lagged Controls	X	X
Year FE	X	X
County FE	X	X
No. of Observations	17,132	17,132
No. of Counties	2,482	2,482
R-Squared	0.99	0.99

Note: In all columns, the dependent variable is the log of the Zillow Home Value Index of the typical value for single-family homes in the ty. Contemporary controls include county population, state GDP growth, and state effective mortgage rate. Lagged controls include the mean debt-to-income ratio of households in the county, the median applicant income in the county, and the median family income in the closest metropolitan area. Standard errors in parentheses are clustered at the county level. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 2.16: Effect of Changes in Income Inequality on One-Bedroom House Prices (2010–2015)

	(1)	(2)
$logGini_{t-1,s}$	0.106***	-0.046
	(0.039)	(0.052)
$logGini_{t-1,s} \times MortgageRate_{t,s}$		0.037***
		(0.009)
Contemporary Controls	X	X
Lagged Controls	X	X
Year FE	X	X
County FE	X	X
No. of Observations	12,355	12,355
No. of Counties	2,240	2,240
R-Squared	0.99	0.99

Note: In all columns, the dependent variable is the log of the Zillow Home Value Index of the typical value for 1-bedroom homes in the county. Contemporary controls include county population, state GDP growth, and state effective mortgage rate. Lagged controls include the mean debt-to-income ratio of households in the county, the median applicant income in the county, and the median family income in the closest metropolitan area. Standard errors in parentheses are clustered at the county level. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 2.17: Effect of Changes in Income Inequality on Two-Bedroom House Prices (2010–2015)

	(1)	(2)
$logGini_{t-1,s}$	0.146***	0.049
	(0.029)	(0.038)
$logGini_{t-1,s} \times MortgageRate_{t,s}$		0.023***
		(0.006)
Contemporary Controls	X	X
Lagged Controls	X	X
Year FE	X	X
County FE	X	X
No. of Observations	13,718	13,718
No. of Counties	2,467	2,467
R-Squared	0.99	0.99

Note: In all columns, the dependent variable is the log of the Zillow Home Value Index of the typical value for 2-bedroom homes in the county. Contemporary controls include county population, state GDP growth, and state effective mortgage rate. Lagged controls include the mean debt-to-income ratio of households in the county, the median applicant income in the county, and the median family income in the closest metropolitan area. Standard errors in parentheses are clustered at the county level. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 2.18: Effect of Changes in Income Inequality on Three-Bedroom House Prices (2010–2015)

	(1)	(2)
$logGini_{t-1,s}$	0.155***	0.062*
	(0.026)	(0.033)
$logGini_{t-1,s} \times MortgageRate_{t,s}$		0.022***
		(0.005)
Contemporary Controls	X	X
Lagged Controls	X	X
Year FE	X	X
County FE	X	X
No. of Observations	13,808	13,808
No. of Counties	2,480	2,480
R-Squared	0.99	0.99

Note: In all columns, the dependent variable is the log of the Zillow Home Value Index of the typical value for 3-bedroom homes in the county. Contemporary controls include county population, state GDP growth, and state effective mortgage rate. Lagged controls include the mean debt-to-income ratio of households in the county, the median applicant income in the county, and the median family income in the closest metropolitan area. Standard errors in parentheses are clustered at the county level. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 2.19: Effect of Changes in Income Inequality on Four-Bedroom House Prices (2010–2015)

	(1)	(2)
$logGini_{t-1,s}$	0.155***	0.096***
	(0.025)	(0.033)
$logGini_{t-1,s} \times MortgageRate_{t,s}$		0.014***
		(0.005)
Contemporary Controls	X	X
Lagged Controls	X	X
Year FE	X	X
County FE	X	X
No. of Observations	13,753	13,753
No. of Counties	2,475	2,475
R-Squared	0.99	0.99

Note: In all columns, the dependent variable is the log of the Zillow Home Value Index of the typical value for 4-bedroom homes in the county. Contemporary controls include county population, state GDP growth, and state effective mortgage rate. Lagged controls include the mean debt-to-income ratio of households in the county, the median applicant income in the county, and the median family income in the closest metropolitan area. Standard errors in parentheses are clustered at the county level. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 2.20: Effect of Changes in Income Inequality on Five-Bedroom House Prices (2010–2015)

	(1)	(2)
$logGini_{t-1,s}$	0.141***	0.072*
	(0.029)	(0.037)
$logGini_{t-1,s} \times MortgageRate_{t,s}$		0.017***
		(0.006)
Contemporary Controls	X	X
Lagged Controls	X	X
Year FE	X	X
County FE	X	X
No. of Observations	13,461	13,461
No. of Counties	2,427	2,427
R-Squared	0.99	0.99

Note: In all columns, the dependent variable is the log of the Zillow Home Value Index of the typical value for 5-bedroom homes in the county. Contemporary controls include county population, state GDP growth, and state effective mortgage rate. Lagged controls include the mean debt-to-income ratio of households in the county, the median applicant income in the county, and the median family income in the closest metropolitan area. Standard errors in parentheses are clustered at the county level. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 2.21: Effect of Changes in Income Inequality on Condo Prices (2010–2015)

	(1)	(2)
$logGini_{t-1,s}$	0.147***	0.101
	(0.051)	(0.063)
$logGini_{t-1,s} \times MortgageRate_{t,s}$		0.011
		(0.009)
Contemporary Controls	X	X
Lagged Controls	X	X
Year FE	X	X
County FE	X	X
No. of Observations	8,238	8,238
No. of Counties	1,487	1,487
R-Squared	0.98	0.98

Note: In all columns, the dependent variable is the log of the Zillow Home Value Index of the typical value for condos in the county. Contemporary controls include county population, state GDP growth, and state effective mortgage rate. Lagged controls include the mean debt-to-income ratio of households in the county, the median applicant income in the county, and the median family income in the closest metropolitan area. Standard errors in parentheses are clustered at the county level. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 2.22: Effect of Changes in Income Inequality on Single-Family House Prices (2010–2015)

	(1)	(2)
$logGini_{t-1,s}$	0.161***	0.082**
	(0.025)	(0.032)
$logGini_{t-1,s} \times MortgageRate_{t,s}$		0.019***
		(0.005)
Contemporary Controls	X	X
Lagged Controls	X	X
Year FE	X	X
County FE	X	X
No. of Observations	13,826	13,826
No. of Counties	2,482	2,482
R-Squared	0.99	0.99

Note: In all columns, the dependent variable is the log of the Zillow Home Value Index of the typical value for single-family homes in the county. Contemporary controls include county population, state GDP growth, and state effective mortgage rate. Lagged controls include the mean debt-to-income ratio of households in the county, the median applicant income in the county, and the median family income in the closest metropolitan area. Standard errors in parentheses are clustered at the county level. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

CHAPTER 3

THE EFFECT OF INCOME INEQUALITY ON MONETARY POLICY EFFECTIVENESS IN THE UNITED STATES

3.1 Introduction

In the past decade, a new interest regarding the effects of monetary policy on income inequality has emerged among macroeconomists. The upward trend in inequality across advanced economies alongside years of loose monetary policy, combined with the evolution of the heterogeneous agent literature, has ignited a query into possible consequences of central banks' policies on income distribution. Interestingly, the other side of this relationship has been mostly neglected. Even though it has been shown that increasing levels of inequality affect the economy in a wide range of ways (see, e.g., Cingano, 2014; Stiglitz, 2012; Jappelli & Pistaferri, 2014), very little has been produced regarding the possible effects of increasing income inequality on monetary policy effectiveness. The aim of this paper is to fill this gap.

Considering the historical levels of income inequality across a selection of US states,[1] I find no statistically significant difference between the response of state personal income and private employment in states with low and high income inequality from 1990:Q1 to 2007:Q4. However, when I use a novel series of quarterly measures of state income inequality, I find that increasing disparities in income distribution have a significant effect on monetary policy effectiveness.[2] A one-percentage-point increase in the Gini coefficient is associated with a smaller change in both state

[1]Due to a lack of data, Delaware, District of Columbia, Hawaii, and Oklahoma are excluded from the analysis.

[2]Monetary policy effectiveness is defined by the size of income and employment response to a monetary shock. A greater response indicates more effectiveness.

personal income and private employment when a monetary policy shock hits the economy. The initial effect is small but significant and increases over time.

These results are obtained by exploring both the cross-sectional variation and the evolution across time of states' income inequality in a panel setting. My first step is to estimate the response of personal income and private employment in each US state when a monetary policy shock hits the economy. This exercise gives a good visual perspective of the asymmetries we find in regional effects of a common monetary policy rule. Afterward, I run a cross-sectional regression with the estimated coefficients against long-run state income inequality to investigate the effect of inequality on an economy's response to a shock.

The main contribution of this paper comes with the final step. I use quarterly US state-level Gini coefficients to evaluate how increasing levels of inequality impact monetary policy effectiveness. To my knowledge, this is the first time in the literature that state inequality data is used at this frequency. I adapt the empirical approach that Leahy and Thapar (2022) have used to estimate how the population structure affects the response of income and employment to monetary policy shocks. It provides a robust methodology to estimate the difference in the effects of monetary policy shocks across high- and low-income inequality regions.

My work supports the ever-growing amount of evidence indicating that central banks should take income distribution into consideration when setting their policies. If increasing levels of income inequality decrease the efficacy of monetary policy, a more unequal economy might need a higher dose of central bank effort to achieve price stability. Moreover, the results also highlight the importance of acknowledging regional disparities of economies subjected to a common rule. Local governments should understand and be prepared for how the policy effect on their economy may deviate from the general expected effect over the common currency union.

By producing a thorough analysis of how increasing income inequality affects monetary policy effectiveness, this paper contributes to the literature that investigates the effects on the economy of higher income disparities. Not only do I provide more clarity to an understudied relationship, but I also introduce quarterly measures of US state inequality to the estimation of response functions to a monetary policy shock. My paper also advances the understanding of regional asymmetries of monetary policy transmission since I underline a neglected channel that influences how local economies respond differently to a monetary shock.

The work that is most similar to this paper is Ma (2021). In the section that investigates the impact of long-run level of inequality on the effectiveness of monetary policy, the author uses US state-level annual data from 1969 to 2006 to estimate a two-step method. First, he uses a three-variable vector autoregressive (VAR) model including the monetary policy shock measure, federal fund rates, and GDP or employment for each state to estimate the effect of the policy on each economy. Then he runs a cross-sectional estimation for the estimated policy effect against long-run averages of income inequality across time for each state. For a robustness check, he also estimates a local projection method for panel data dividing states into high and low inequality groups. For both analyses, the results show that increasing income inequality decreases monetary policy effectiveness.

My analysis differs from the work of Ma (2021) in a few key aspects. First, instead of using annual data from 1969 to 2006, I use quarterly data from 1990:Q1 to 2007:Q4. Second, I use the local projection method to estimate the first of the two steps of the method he proposes. Finally and most importantly, I extend the analysis, introducing a different methodology to evaluate the effects of changes in short-term income inequality.

There are not many other papers investigating how income inequality might affect monetary policy, and their results are not homogeneous. Voinea et al. (2018), for example, have found that lower inequality is associated with stronger effectiveness and higher homogeneity of monetary policy transmission in Romania. Kim (2019) has also suggested that the real effects of monetary policy shocks can decrease if the poorer class consists of a larger share of the population in an economy. However, using a quantitative New-Keynesian model with heterogeneous households, Cravino et al. (2020) have shown that the responses of aggregate prices and output to monetary policy are not impacted by significant changes in the level of income inequality.

It is clear that more research is needed to understand how changes in income distribution could affect monetary policy effectiveness. This chapter is a contribution to the debate and is organized as follows: Section 3.2 provides a quick overview of the channels through which inequality might affect monetary policy transmission. Section 3.3 defines the methodology and data used in the empirical strategy. Section 3.4 discusses the results. Finally, section 3.5 provides a conclusion.

3.2 Income Inequality and Monetary Policy

The few works that have found a significant effect of increasing income inequality on the transmission of monetary policy offer different explanations for the mechanisms behind the relationship. For example, the hypothesis upon which Voinea et al. (2018) build their analysis is that monetary policy is less effective when inequality is high because it does not reach a large share of the population, which is unable to borrow. They argue that household response to changes in monetary conditions depends on their income and indebtedness profile. Debt service is an important determinant of the consumption behavior and allows monetary policy to influence the aggregate demand. Therefore, as inequality increases and fewer households have access to credit, monetary policy becomes less effective.

Instead of focusing on the demand side of the economy, Ma (2021) has proposed that changes in income inequality affect monetary policy effectiveness through a labor supply channel. In their heterogeneous agent model, a reservation wage for each household can be computed under the indivisible labor supply assumption, and its distribution determines aggregate labor supply elasticity in the economy. Consequently, a more homogeneous distribution of workers is associated with larger labor supply elasticity since the reservation wage distribution is more concentrated, which implies that there are more marginal workers placed around the market wage. As a result, a more equal economy has a larger size of labor supply elasticity, which will be the key linkage between the level of income inequality and the effectiveness of monetary policy. Since labor supply is more elastic when inequality is lower, the response of hours is larger in low-inequality economies compared to economies with higher inequality, increasing monetary policy effectiveness.

There is also another interpretation of the results derived from the model in Ma (2021). Since there is a negative relationship between the slope of the New Keynesian Philips curve and the labor supply elasticity, higher labor supply elasticity in the low-inequality economy leads to a flatter New Keynesian Philips curve. Hence, it generates the larger real effects of monetary policy shocks on the economy with lower inequality. The flatter New Keynesian Philips curve in the low-inequality economy leads inflation to increase to a lesser degree than in a high-inequality economy.

It is possible that both channels play a role in how income inequality affects the economy's response to a monetary policy shock. In advanced economies in which the financial sector is more developed, even low-income households may have access to some degree of credit. Therefore, the demand channel might not be as strong as the supply channel. On the other hand, in some emerging and poor economies, not only low-income but also middle-income households might have difficulty accessing the financial market. In those economies, the effect of rising inequality on monetary policy transmission through this channel might be stronger.

3.3 Empirical Strategy

Here we consider the United States, where there is ample variation of measured income inequality across all states. Nonetheless, US states are subject to the same monetary rule because they form a monetary union. This scenario provides an opportunity for a panel analysis of how each state's economy, given its level of income inequality, reacts to a common monetary policy shock.[3]

There are many advantages for considering a monetary union over a set of countries subject to their own monetary policy rules. The most obvious is the existence of only one monetary policy rule affecting every economy instead of several different rules. Consequently, there is no need to work on the identification of different shocks across countries, which could lead to several estimation issues. Moreover, the chances that the monetary policy will react to changes in the income distribution of a specific state are virtually null. Finally, even though there is some degree of heterogeneity across states' economies, they also have a homogeneous legal and institutional structure.

Considering US states as a panel of economies, I can explore both the cross-sectional variation and the evolution across time of states' income inequality. I start by estimating the response of personal income and private employment in

[3]As Leahy and Thapar (2022) suggest, in this framework, we can remove the first-order effect of monetary policy using time-fixed effects.

each US state when a monetary policy shock hits the economy. Then I run a cross-sectional regression with the estimated coefficients against long-run state income inequality to investigate the effect of inequality on an economy's response to a shock. As a robustness check of this analysis, I separately estimate the impulse response functions of low- and high-income inequality states in two different panel implementations. Finally, I adapt the empirical approach that Leahy and Thapar (2022) have used to estimate how the population structure affects the response of income and employment to monetary policy shocks. I use the variation across US states and across time in the measure of income inequality to evaluate how increasing levels of inequality impact monetary policy effectiveness.

In the remainder of this section, I explain in detail the models used to implement the empirical strategy. Subsequently, I briefly discuss the identification of monetary policy shocks and provide a description of the data used in the analysis.

3.3.1 Model Specification

The empirical implementation in Ma (2021) is the work that is most similar to this paper. To estimate the impact of the long-run level of inequality on the effectiveness of monetary policy, the author employs a two-step approach. In the first step, he considers a three-variable VAR model including the monetary policy shock measure, federal fund rates, and GDP or employment at annual frequency for each state. He estimates the impact of the shock on both state GDP and employment and then, in a cross-sectional estimation, regresses the estimated coefficients on measures of inequality, which are long-run averages across time for each state.

Instead of using a VAR model to estimate how each state's economy reacts to a monetary policy shock, I use the local projection method proposed by Jordà (2005).

This method estimates regressions of the dependent variable at horizon $t+h$ on the shock in period t and uses the coefficient on the shock as the impulse response estimate. I follow the specification in Ramey (2016), but I adapt it to a state-level analysis and run the following equation:

$$log[X_{t+h}] = \alpha^h \epsilon_t^m + \sum_{j=1}^{J} \beta^j \epsilon_{t-j}^m + \sum_{j=1}^{J} \delta^j ffr_{t-j} + \sum_{j=1}^{J} \gamma^j Z_{t-j} + u_{t+h}. \tag{3.1}$$

The dependent variable X is either state personal income or state private employment, and $h = 1, 2, ..., H$ represents the horizon. ϵ_t^m is the monetary policy shock, ffr represents the level of the federal funds rate, and Z includes lags of X, current and lagged employment share in manufacturing, construction, and financial activities, current and lagged population, house price index, and the fraction of mortgages that are adjustable-rate mortgages.[4]

After I estimate equation (3.1) for each state, I follow Ma (2021) and investigate the relationship between the long-run level of income inequality and the effectiveness of monetary policy across states using a simple cross-sectional method. The effectiveness of monetary policy is measured by the peak personal income or private employment response to the shock, which usually occurs between the sixth and the 12th quarter. Hence, the estimated equation is:

$$\alpha_s^h = \zeta_s + Ineq_s + log[PerCap]_s + u_s, \tag{3.2}$$

where α_s^h is the state personal income or private employment response to the monetary policy shock at the sixth, eighth, 10th, or 12th quarter; $Ineq_s$ is the average

[4]Except for horizon $h = 0$, the error term u_{t+h} is serially correlated because it is a moving average of the forecast errors from t to $t+h$. To account for this serial correlation in the residuals, I estimate Newey-West standard errors.

of a measure of state income inequality over the period previously analyzed; and $log[PerCap]_s$ the log of the average of state personal income per capita.

As a robustness check of this analysis, I follow Ma (2021) once again and estimate the local projection method for panel data, separating the states into two samples: high and low inequality.[5] The estimated equation below is a panel version of equation (3.1), with the same variables but incorporating state-fixed effects, θ_i, which can control for unobserved cross-state heterogeneity.

$$log[X_{s,t+h}] = \alpha^h \epsilon_t^m + \sum_{j=1}^{J} \beta^j \epsilon_{t-j}^m + \sum_{j=1}^{J} \delta^j ffr_{t-j} + \sum_{j=1}^{J} \gamma^j Z_{s,t-j} + \theta_s + u_{s,t+h} \quad (3.3)$$

Finally, to investigate how changes in short-term income inequality might affect the effectiveness of monetary policy, I build on the work of Leahy and Thapar (2022). In their paper, they use another panel version of the Jorda projection to estimate how the population structure affects the response of income and employment to monetary policy shocks. Following their methodology, I estimate the model below:

$$\Delta log[X_{s,t+h}] = \alpha^h \epsilon_t^m Gini_{s,t-1} + \phi Gini_{s,t-1} + \sum_{j=1}^{J} \gamma^j Z_{s,t-j} + \theta_s + \delta_t + u_{s,t+h}. \quad (3.4)$$

X, ϵ_t^m, and the variables included in Z are the same as discussed above. The two main innovations in equation (3.4) are the inclusion of a change in X_s between period $t-1$ and period $t+h$, and the interaction between the monetary policy shock and the states' Gini coefficient in period $t-1$ (which measures income inequality quarterly).[6] With this new specification, the coefficient of interest α^h measures the

[5] I estimate samples with top and bottom five, 10, and 20 states.

[6] I also include time-fixed effects δ_t and therefore do not include the monetary policy shock ϵ_t^m separately in the regression. The time-fixed effects account for factors that are common to all states such as interest rates, the exchange rate, and aggregate inflation.

effect over time of a one-percentage-point increase in the Gini coefficient on the responsiveness of the growth rate of state personal income (or private employment) to a positive monetary policy shock.

In my analysis, a positive monetary policy shock is a contractionary policy because it represents a shock to interest rates. Consequently, if I find that α^h is positive, then an increase in income inequality reduces the effect of a shock to monetary policy on X. In other words, higher inequality is associated with lower monetary policy effectiveness. In contrast, if α^h is negative, it means that as income inequality increases, monetary policy becomes more effective.

3.3.2 Data

There are several ways to identify and measure monetary policy shocks and no consensus in the literature as to which is the best alternative.[7] In this paper, I use the Romer and Romer (2004) monetary policy shock series updated and summed to a quarterly frequency by Wieland and Yang (2020). Romer and Romer (2004) combined the use of Greenbook forecasts with narrative methods to construct their measure of monetary policy shocks. The shocks are residuals from a regression of the federal funds rate on lagged values and the Federal Reserve's information set based on Greenbook forecasts. The authors argue that these are plausibly exogenous with respect to the evolution of economic activity. My period of analysis is from 1990:Q1 to 2007:Q4 due to limited quarterly state-level data and to avoid the zero lower bound on interest rates.

[7] See Ramey (2016) for a great discussion on monetary policy shocks and their propagation.

The first choice of variables to evaluate monetary policy effectiveness would be state-level GDP and aggregate consumption. However, these estimates are only available on a quarterly frequency from 2005 on. Thus, following Leahy and Thapar (2022), I use the next-best options, which are state personal income and private employment. The data on state personal income comes from the Regional Economic Accounts program at the Bureau of Economic Analysis. There are no state-level price indices available for period analyzed, so I use nominal personal income. The data for state private employment is obtained from the Current Employment Statistics program conducted by the Bureau of Labor Statistics (BLS). It is published at a monthly frequency, so I average to a quarterly frequency.

The remainder of the state-level data is at an annual frequency, except for one measure of income inequality discussed in the next subsection. I assume that each remains constant within the calendar year. State population data is obtained from the Census Bureau. I also use data on the fraction of mortgages that are adjustable-rate mortgages from the Federal Housing Finance Agency's Monthly Interest Rate Survey. Finally, for house prices, I use the Federal Housing Finance Agency's seasonally adjusted purchase-only house price index. The index is estimated using sales price data for single-family houses whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac.

3.3.2.1 Quarterly Gini Coefficient

One of the contributions of this paper is to use quarterly state-level income inequality data, more specifically the Gini coefficient, for the first time in an analysis of monetary policy effects across US states. These coefficients are estimated by Fischer et al. (2021) for the period starting in 1985:Q1 to 2017:Q1, but as mentioned before, I only use data from 1990:Q1 to 2007:Q4.[8] To construct state-level Gini coefficients, Fischer and colleagues use household income data from the Annual Social and Economic Supplement of the Current Population Survey (CPS). They first estimate an annual measure of income inequality and then interpolate it to the quarterly frequency using splines.

The alternative to using a quarterly Gini coefficient is to use the annual estimates of the Gini coefficient, the income share of the top 10% of the population, the Atkinson index, the relative mean deviation of income, and the Theil index constructed by M. Frank (2014). These inequality measures are constructed using data published in the IRS's Statistics of Income on the number of returns and adjusted gross income (before taxes) by state and by size of the adjusted gross income. Both the quarterly and the annual data are pre-tax estimates and should yield similar results. However, figure 3.1 shows that the correlation between the Gini coefficients at quarterly and annual frequencies is not high. Hence, even though the main analysis of this paper relies on quarterly income inequality measures, I also use annual estimates for robustness checks.

3.4 Results

3.4.1 Monetary Policy Transmission across US States

The starting point of this analysis is the evaluation of how personal income and private employment across US states respond to a common monetary policy shock. Figure 3.2 shows the impulse response functions (IRFs) for selected states from

[8] I would like to thank Dr. Manfred M. Fischer, Dr. Florian Huber, and Dr. Michael Pfarrhofer for kindly providing me the data.

Figure 3.1: Comparing State Gini Coefficients of Different Frequencies

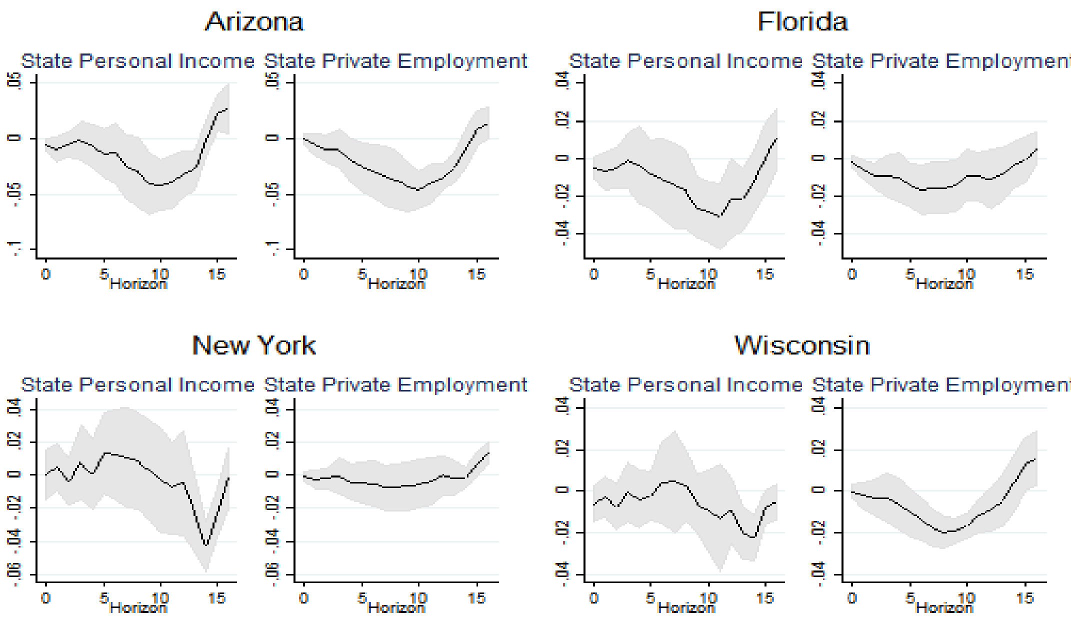
Note: Annual Gini estimated by M. Frank (2014) and quarterly Gini estimated by Fischer et al. (2021).

different Census regions. As expected, a contractionary shock leads to a decrease in both personal income and private employment over time.[9] However, the evolution of the response function and the magnitude of the economy's reaction vary across states.

The literature shows that many factors could contribute to the disparity of the effect of monetary policy across a common currency union. Since monetary contraction reduces the demand for capital and durable goods, regional differences in the mix of interest-sensitive industries could affect policy transmission. Moreover, differences in house market characteristics could also play a role. Because monetary policy shocks affect the cost of new and adjustable-rate mortgages, heterogeneity across states will generate different responses in aggregate consumption. Diverse effects could arise from changes in house prices and residential investments as well.

[9]This is not the case for every state. In some states, income and/or employment rise after a positive monetary policy. See appendix A for the IRFs of every state.

Figure 3.2: Monetary Policy Shock Transmission on Selected States



Note: Shaded area represents the 95% confidence interval. X-axes show quarters after the shock. Newey-West standard errors are used.

Another factor that could fuel regional asymmetries in monetary policy transmission is the difference in the composition of small and large banks within an economy. Since small firms usually face higher information and transaction costs to meet their credit needs, and small banks are more limited than large banks in their ability to find alternative sources of funding and therefore to make loans, regions with a larger share of big banks experience a more effective monetary policy transmission.

There are possibly other elements influencing the effectiveness of monetary policy across US states. The remainder of this section is an investigation into the role that income inequality might play in this.

3.4.2 Effect of Long-Run Inequality: A Two-Step Estimation

First, I consider the effect of long-run income inequality on the effectiveness of monetary policy, which is measured by the peak response of personal income and private employment to contractionary monetary policy shocks. Long-run level of inequality is defined as the average value of both the annual and quarterly Gini coefficients and also the annual measures of the income share of the top 10% of the population, the Atkinson index, the relative mean deviation of income, and the Theil index between 1990 and 2007.

Considering that the peak response of the economy usually occurs from the sixth quarter on, I initially investigate the correlation between the effect of a shock on personal income and private employment over that period and the several measures of inequality. It should be noted that since the shock is contractionary, a positive relationship means that higher inequality is associated with lower monetary policy effectiveness, whereas a negative relationship implies the opposite. Tables 3.1 and 3.2 show the results. For both income and employment, the correlation coefficients are small, indicating a weak relationship. Still, several interesting elements should be highlighted. First, depending on the horizon, inequality seems to either increase or decrease the effect of a shock on personal income. Second, almost every result for private employment indicates income inequality diminishing monetary policy effectiveness. This effect grows stronger the longer the horizon.

To further investigate these findings, I estimate equation (3.1) with the responses from after eight and 10 quarters and income inequality measured by the long-run av-

Table 3.1: Correlation between Income Inequality Measures and Personal Income Changes after Specific Quarters

	Personal Income Change					
	Q6	Q8	Q10	Q12	Q14	Q16
Quarterly Gini Coefficient	0.013	-0.088	0-.124	0.093	0.014	0.014
Annual Gini Coefficient	-0.049	-0.124	-0.131	-0.139	0.059	0.174
Top 10%	0.016	0.025	-0.274	-0.265	-0.163	0.057
Atkinson Index	0.085	0.073	-0.196	-0.287	-0.236	0.065
Relative Mean Deviation	0.071	0.010	-0.141	-0.213	-0.119	0.107
Theil Index	0.031	0.032	-0.241	-0.324	-0.211	0.086

Note: Quarterly Gini coefficients are estimated by Fischer et al. (2021). The other measures are estimated by M. Frank (2014).

Table 3.2: Correlation between Income Inequality Measures and Private Employment Changes after Specific Quarters

	Private Employment Change					
	Q6	Q8	Q10	Q12	Q14	Q16
Quarterly Gini Coefficient	-0.135	-0.099	-0.008	0.068	0.137	0.285
Annual Gini Coefficient	-0.027	0.036	0.099	0.033	0.072	0.093
Top 10%	0.087	0.124	0.115	0.063	0.153	0.230
Atkinson Index	0.126	0.164	0.138	0.059	0.117	0.133
Relative Mean Deviation	0.052	0.104	0.122	0.041	0.096	0.115
Theil Index	0.122	0.163	0.129	0.044	0.103	0.116

Note: Quarterly Gini coefficients are estimated by Fischer et al. (2021). The other measures are estimated by M. Frank (2014).

erage of quarterly Gini.[10] The results presented in tables 3.3 and 3.4 show a negative effect of inequality, which indicates that higher inequality levels are associated with higher monetary policy effectiveness. However, the coefficient is not statistically significant in any of the specifications. These findings do not confirm the results of Ma (2021), who has estimated a statistically significant inverse relationship between state GDP and employment responses and long-run income inequality, in that case meaning that higher inequality decreases the effect of monetary policy.

Table 3.3: Cross-Section Estimation of Long-Run Inequality Effect

	State Personal Income			
	(Q8)	(Q8)	(Q10)	(Q10)
Quarterly Gini	-0.0007	-0.0007	-0.0009	-0.0008
$(Long - Run\ Average)$	(0.001)	(0.001)	(0.001)	(0.001)
Income per Capita		0.040**		0.009
		(0.015)		(0.015)
No. of Observations	47	47	47	47
R-Squared	0.02	0.11	0.01	0.02

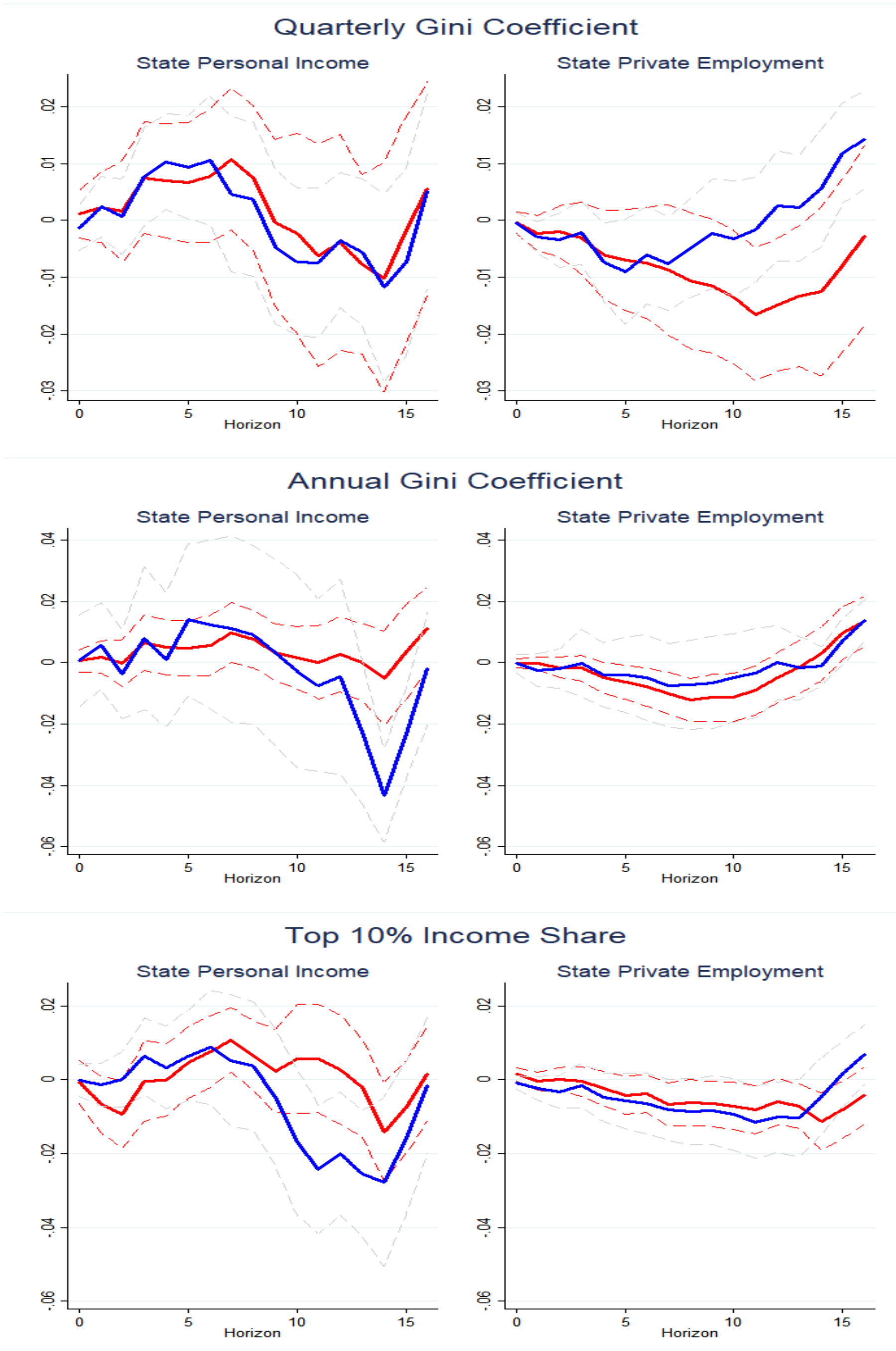
Note: The dependent variable is the change in state personal income eight or 10 quarters after a monetary policy hits the economy. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Another way to observe that the difference between the responses of economies in states with higher and lower historical income inequality is not statistically significant is to separate those states into two groups and estimate the local projection method for panel data for each group separately. Figure 3.3 shows the IRFs for the bottom and top five states with lowest and highest inequality measures. The difference between the responses is not significant in any of the specifications.[11]

[10] I also run the regression for other quarters and inequality measures. The results can be found in appendix B.

[11] The results for the bottom and top 10 states are also not statistically significant. See results in appendix C.

Figure 3.3: Monetary Policy Transmission on Top/Bottom Five States with Highest/Lowest Inequality



Note: Blue line represents the IRF of the five states with higher income inequality. Red line represents the IRF of the five states with lower income inequality. Dashed lines delimit the 95% confidence intervals. X-axes show quarters after the shock. Newey-West standard errors are used. Annual Gini and top 10% income share estimated by M. Frank (2014). Quarterly Gini estimated by Fischer et al. (2021).

Table 3.4: Cross-Section Estimation of Long-Run Inequality Effect

	State Private Employment			
	(Q8)	(Q8)	(Q10)	(Q10)
Quarterly Gini	-0.0006	-0.0005	-0.0001	-0.00005
(Long − Run Average)	(0.0008)	(0.0008)	(0.0009)	(0.0008)
Income per Capita		0.023*		0.017
		(0.012)		(0.012)
No. of Observations	47	47	47	47
R-Squared	0.01	0.05	0.02	0.003

Note: The dependent variable is the change in state private employment eight or 10 quarters after a monetary policy hits the economy. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

3.4.3 Panel Analysis with Quarterly Gini Coefficients

Long-run income inequality might have no impact on the effectiveness of monetary policy; nonetheless, it is still possible that short-term changes to inequality affect how the economy responds to a monetary shock. This is indeed the result I find when I estimate equation (3.4) using quarterly Gini coefficients as a measure of income inequality. Figure 3.4 presents the effect over time of a one-percentage-point increase in the Gini coefficient on the responsiveness of the growth rate of state personal income and private employment to a positive monetary policy shock. As mentioned, since the shock in the analysis is contractionary, a positive coefficient means that an increase in inequality reduces the effect of the shock.

The results indicate that both personal income and private employment react more strongly when income inequality is lower. The positive coefficients for the Gini imply that if inequality increases, then an unanticipated hike in interest rates raises personal income after eight quarters and private employment after 11 quarters relative to the effect that monetary policy has on average on the US economy. This does not imply that income and employment will rise because the total effect of

Figure 3.4: Effect of Income Inequality on Monetary Policy Effectiveness

Note: Shaded area represents the 95% confidence interval. X-axes show quarters after the shock. Newey-West standard errors are used.

the monetary policy shock on state income is a combination of the first-order effect, which is assimilated into the time effect, and the interaction effect, which is considered here. Since an increase in interest rates is expected to reduce personal income and private employment, a positive coefficient indicates that monetary tightening has a weaker negative effect when inequality is higher.

3.5 Conclusion

Economists' understanding of the monetary policy effect over income inequality has substantially increased over the past decade with many papers dedicated to investigating this issue. However, the opposite side of the relationship has been neglected, and still little is known. This work helps to illuminate this topic and shows that it should not be ignored because changes in income inequality have significant effects on monetary policy transmission, with higher inequality associated with lower policy effectiveness.

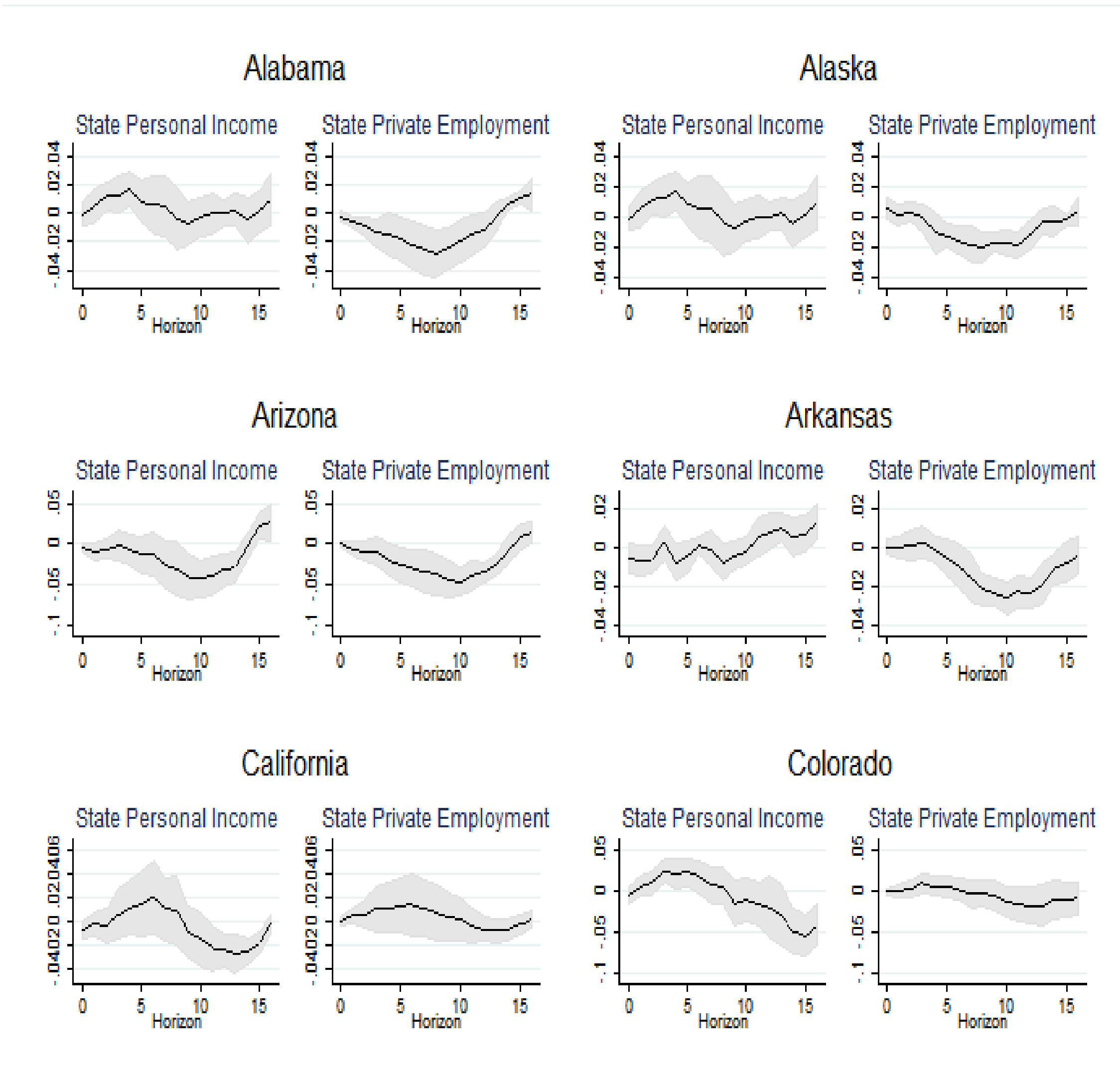
This result has many policy implications. There is a debate whether central banks should care that their policies may be worsening income distribution since the pursuit of a more equal economy is not part of their mandates. However, if changes in income inequality affect monetary policy transmission, then an increase in the income gap is relevant to the policymakers' goal and should be considered when the policy is designed.

Furthermore, the fact that states are affected differently by the same monetary policy rule because of distinct levels of inequality is of great importance for local governments. State authorities have no control over monetary policy, but they may enact policies that affect the local income inequality and lead to a more equal distribution of income. In doing so, monetary policy will be more effective in that state's economy.

This analysis was not focused on formalizing a theoretical framework to understand how income inequality affects monetary policy. I only presented two possible channels in demand and supply that could play a role. Therefore, a natural extension of this research is to integrate both channels into one general equilibrium model to evaluate the contributions of each to the overall effect of inequality on monetary policy effectiveness.

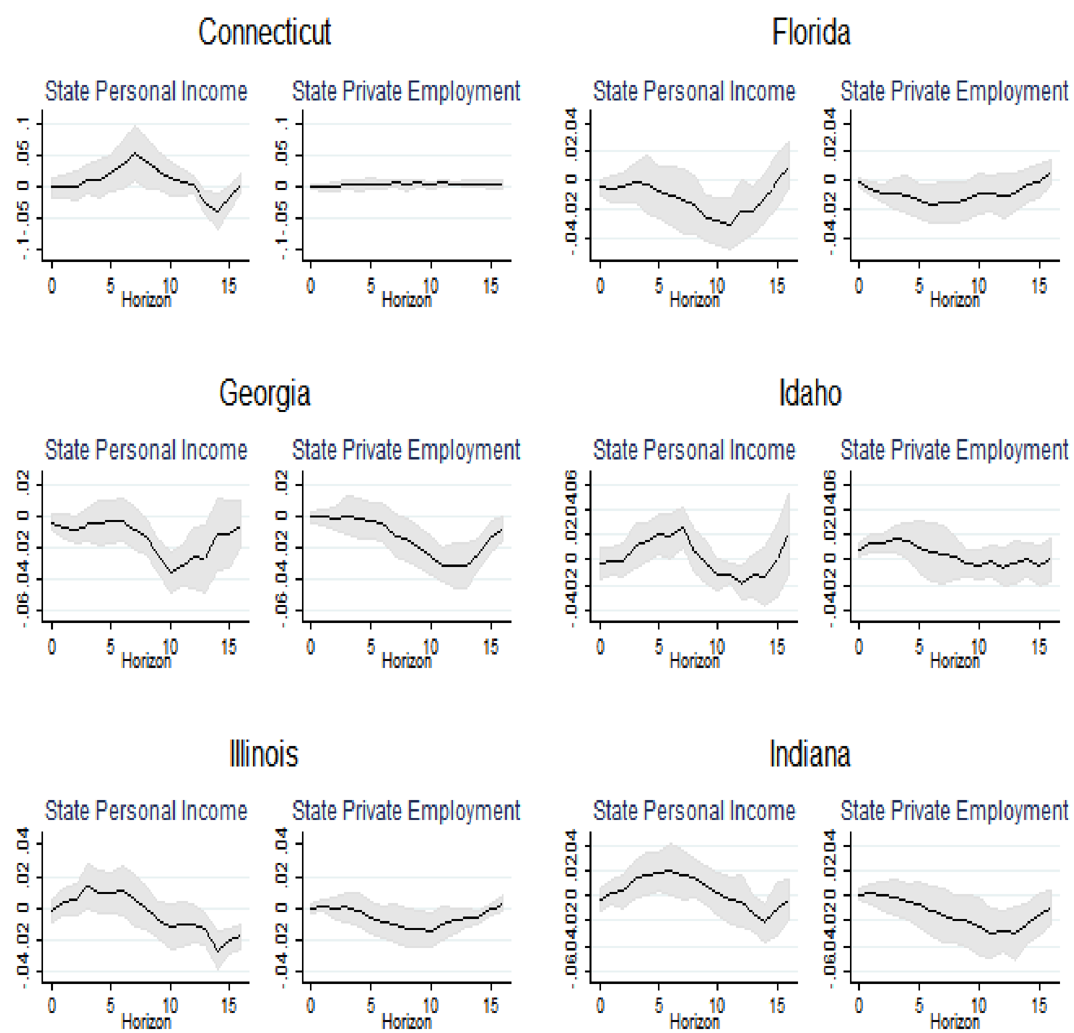
3.6 Appendix A: Monetary Policy Transmission across US States

Figure 3.5: Monetary Policy Shock Transmission in Each US State



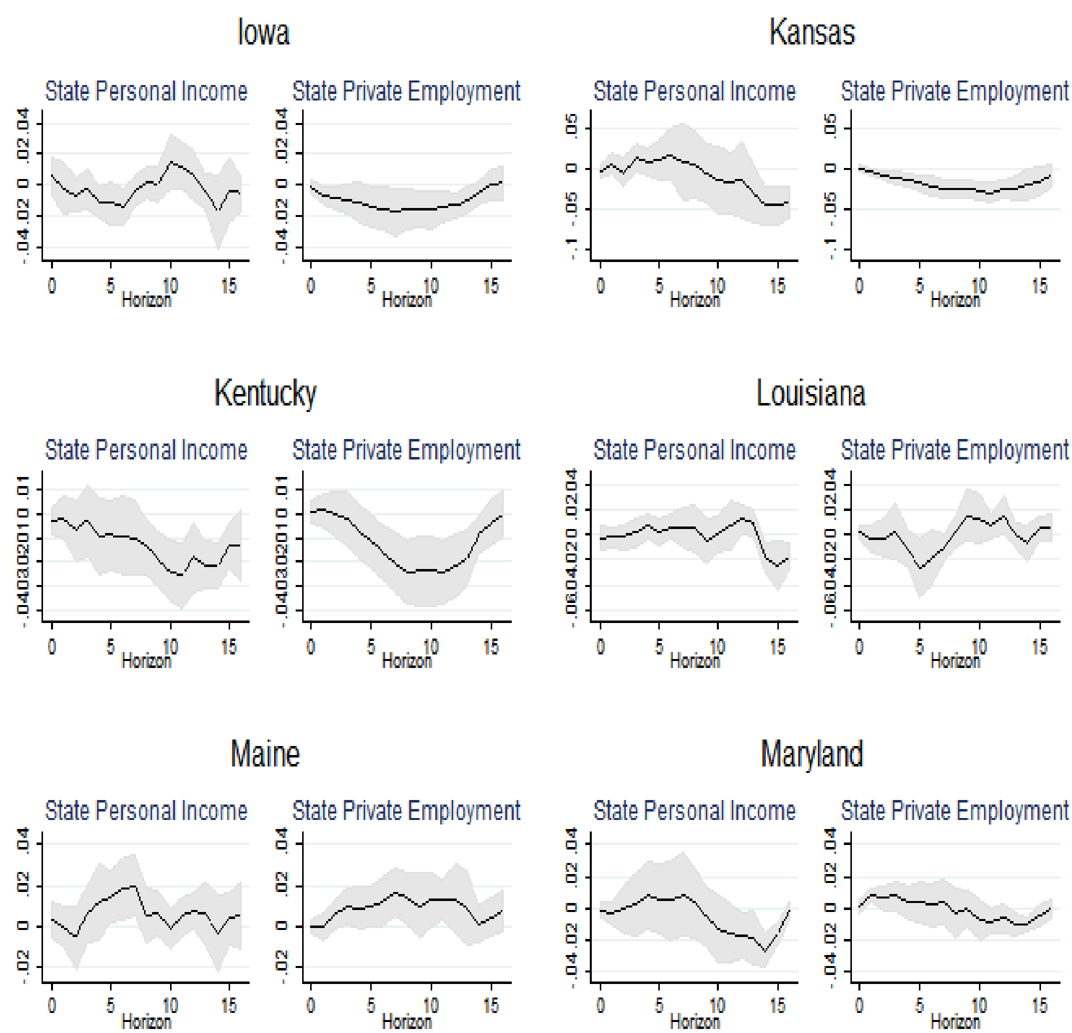
Note: Shaded area represents the 95% confidence interval. X-axes show quarters after the shock. Newey-West standard errors are used.

Monetary Policy Shock Transmission in Each US State–Continuation



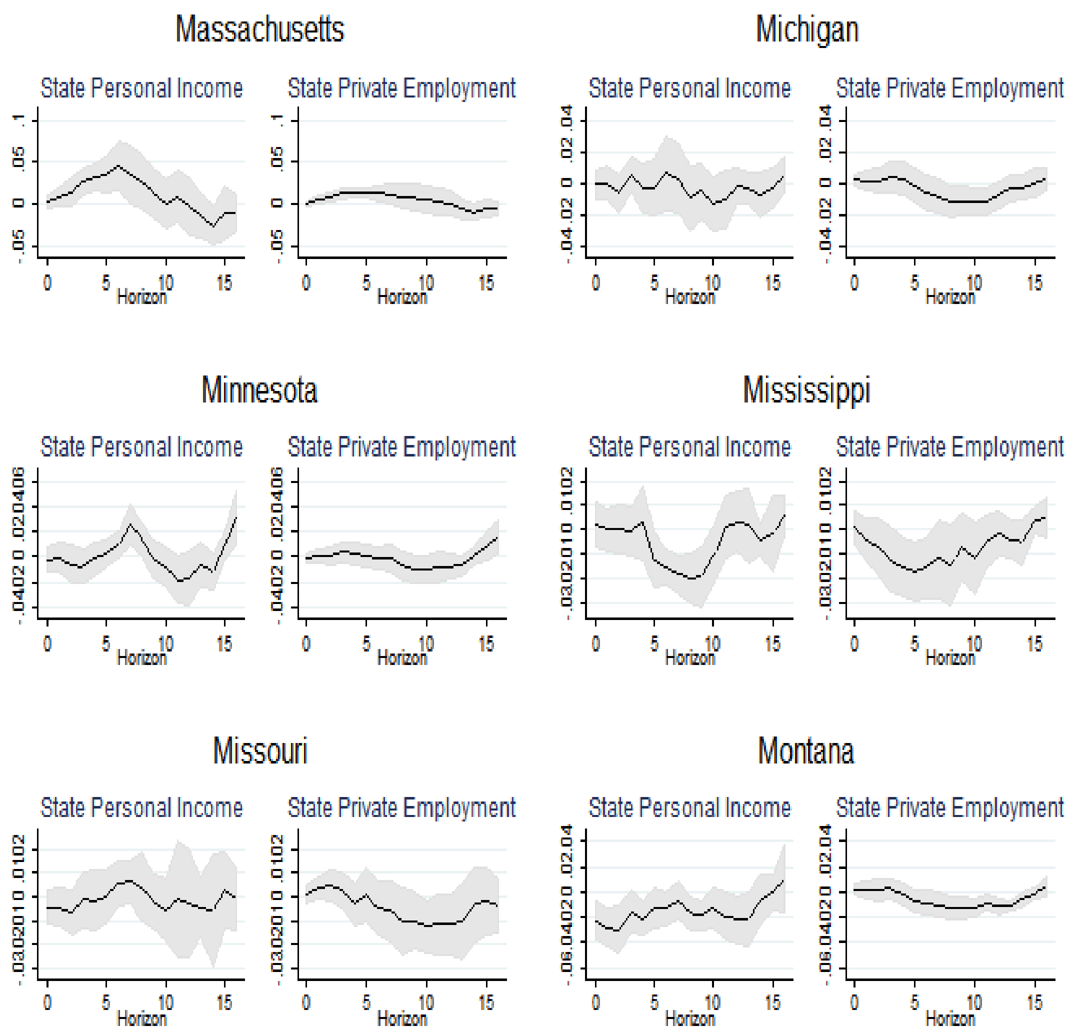
Note: Shaded area represents the 95% confidence interval. X-axes show quarters after the shock. Newey-West standard errors are used.

Monetary Policy Shock Transmission in Each US State–Continuation



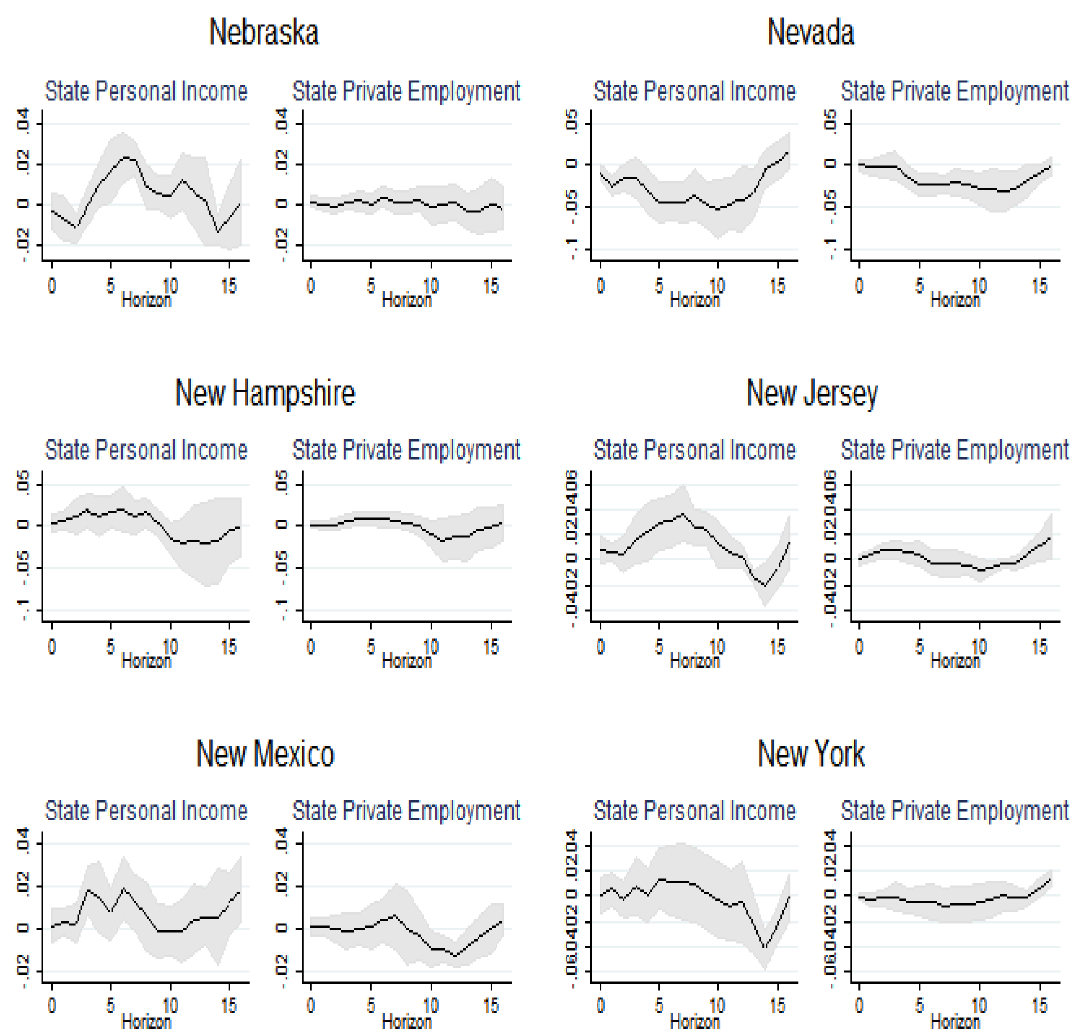
Note: Shaded area represents the 95% confidence interval. X-axes show quarters after the shock. Newey-West standard errors are used.

Monetary Policy Shock Transmission in Each US State–Continuation



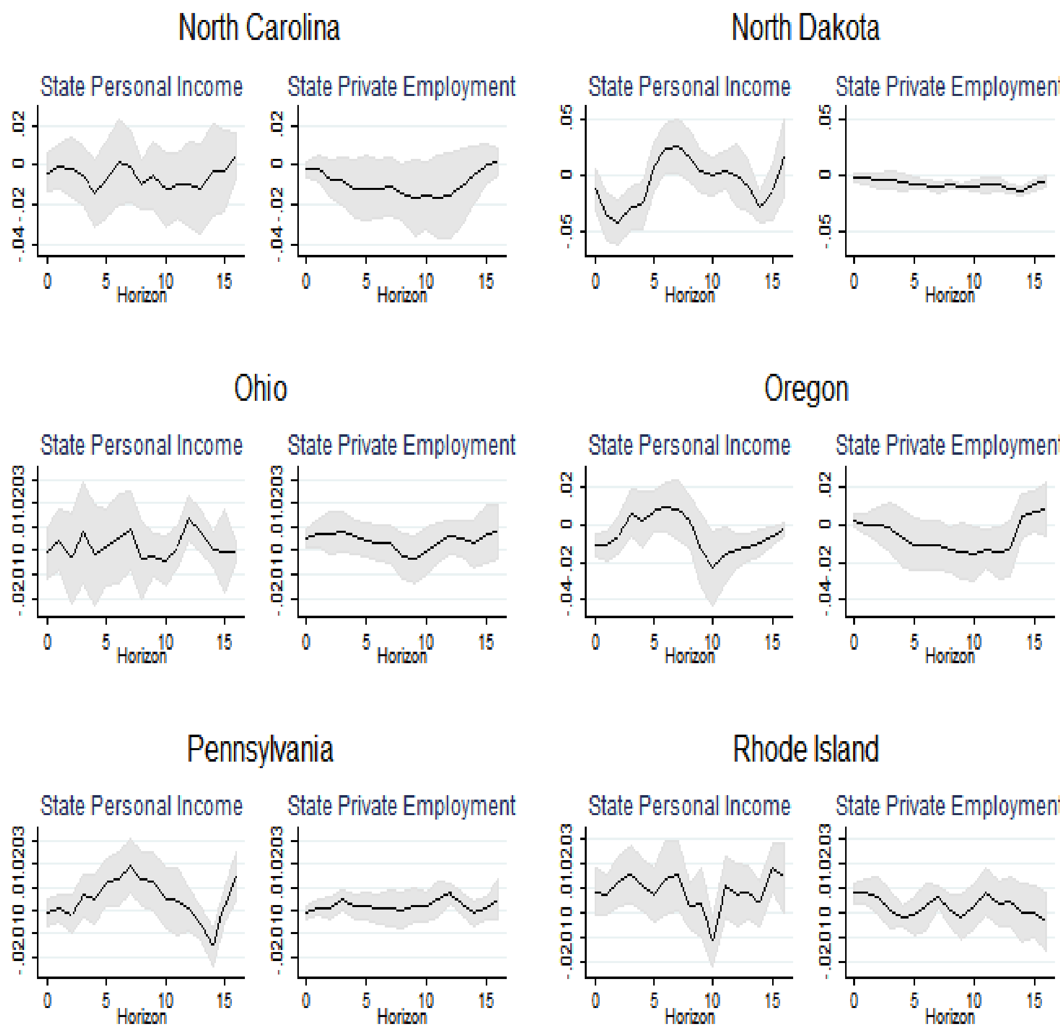
Note: Shaded area represents the 95% confidence interval. X-axes show quarters after the shock. Newey-West standard errors are used.

Monetary Policy Shock Transmission in Each US State–Continuation



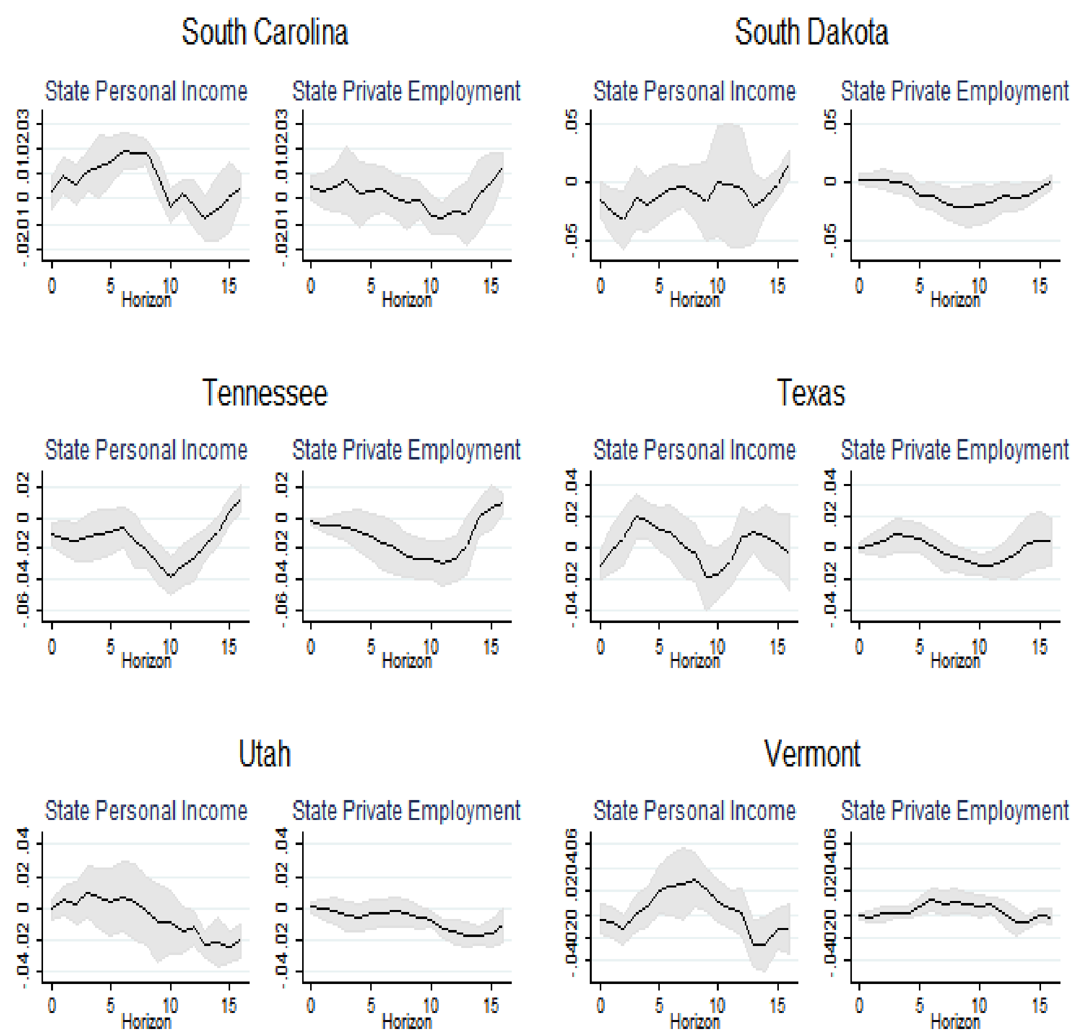
Note: Shaded area represents the 95% confidence interval. X-axes show quarters after the shock. Newey-West standard errors are used.

Monetary Policy Shock Transmission in Each US State–Continuation



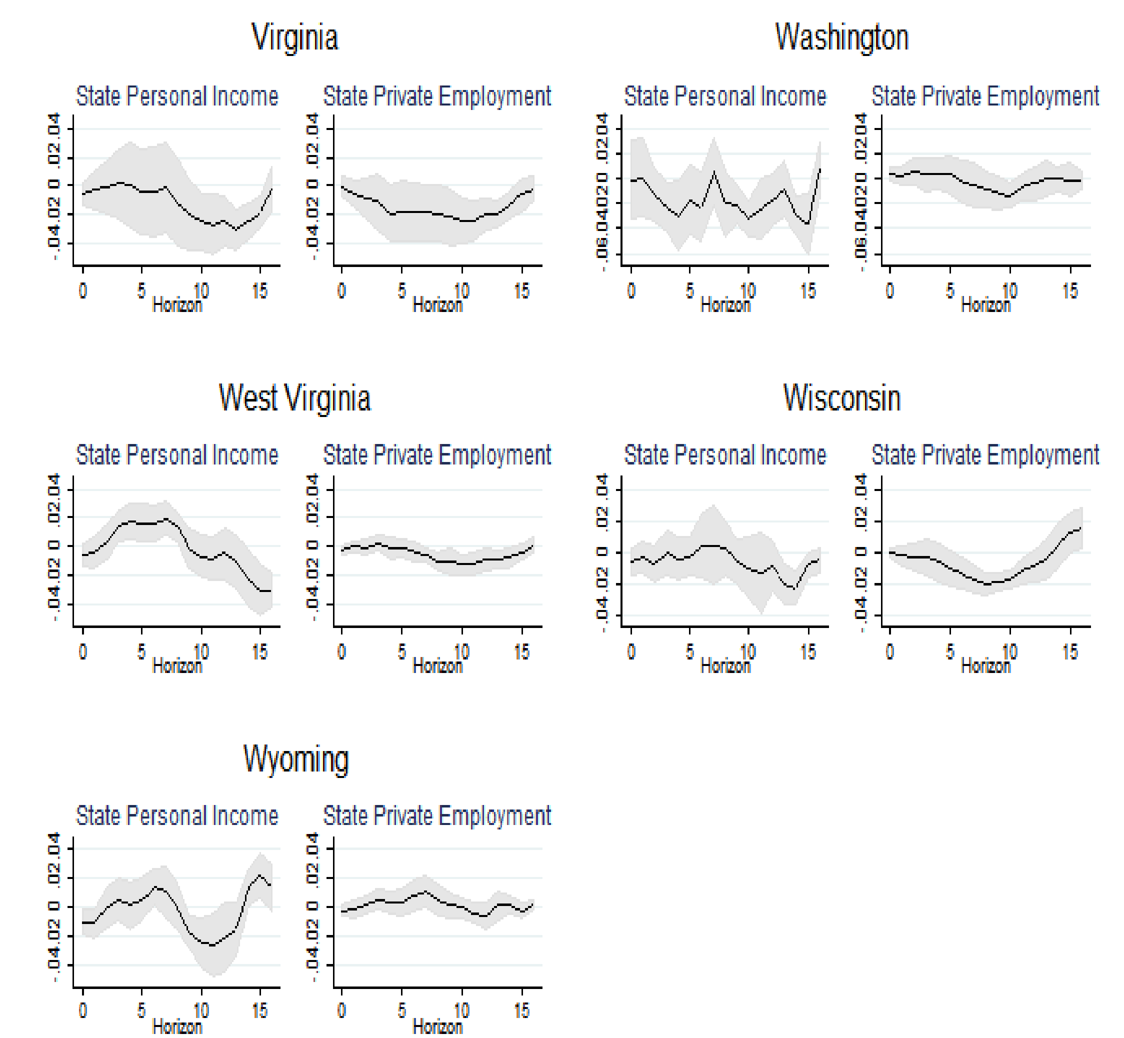
Note: Shaded area represents the 95% confidence interval. X-axes show quarters after the shock. Newey-West standard errors are used.

Monetary Policy Shock Transmission in Each US State–Continuation



Note: Shaded area represents the 95% confidence interval. X-axes show quarters after the shock. Newey-West standard errors are used.

Monetary Policy Shock Transmission in Each US State–Continuation



Note: Shaded area represents the 95% confidence interval. X-axes show quarters after the shock. Newey-West standard errors are used.

3.7 Appendix B: Cross-Section Estimations of Long-Run Inequality Effects

Table 3.5: Cross-Section Estimation of Long-Run Inequality Effect–A

	State Personal Income			
	(Q6)	(Q6)	(Q12)	(Q12)
Quarterly Gini	0.0001	0.00009	0.0006	0.0006
$(Long - Run\ Average)$	(0.001)	(0.0011)	(0.0009)	(0.0009)
Income per Capita		0.037**		-0.012
		(0.017)		(0.013)
No. of Observations	47	47	47	47
R-Squared	0.02	0.06	0.01	0.02

Note: The dependent variable is the change in state personal income six or 12 quarters after a monetary policy hits the economy. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 3.6: Cross-Section Estimation of Long-Run Inequality Effect–B

	State Private Employment			
	(Q6)	(Q6)	(Q12)	(Q12)
Quarterly Gini	-0.0007	-0.0007	0.0004	0.0004
$(Long - Run\ Average)$	(0.0007)	(0.0007)	(0.0008)	(0.0008)
Income per Capita		0.022**		0.015
		(0.011)		(0.012)
No. of Observations	47	47	47	47
R-Squared	0.004	0.06	0.02	0.004

Note: The dependent variable is the change in state private employment six or 12 quarters after a monetary policy hits the economy. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 3.7: Cross-Section Estimation of Long-Run Inequality Effect–C

	State Personal Income			
	(Q6)	(Q6)	(Q8)	(Q8)
Annual Gini	-0.0004	-0.0007	-0.0008	-0.001
(Long − Run Average)	(0.001)	(0.001)	(0.0009)	(0.0009)
Income per Capita		0.039**		0.044***
		(0.017)		(0.015)
No. of Observations	47	47	47	47
R-Squared	0.02	0.07	0.01	0.13

Note: The dependent variable is the change in state personal income six or eight quarters after a monetary policy hits the economy. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 3.8: Cross-Section Estimation of Long-Run Inequality Effect–D

	State Private Employment			
	(Q6)	(Q6)	(Q8)	(Q8)
Annual Gini	-0.0001	-0.0004	0.0002	-0.00006
(Long − Run Average)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Income per Capita		0.023**		0.023*
		(0.011)		(0.012)
No. of Observations	47	47	47	47
R-Squared	0.02	0.05	0.02	0.04

Note: The dependent variable is the change in state private employment six or eight quarters after a monetary policy hits the economy. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 3.9: Cross-Section Estimation of Long-Run Inequality Effect–E

	State Personal Income			
	(Q10)	(Q10)	(Q12)	(Q12)
Annual Gini	-0.0008	-0.0009	-0.0007	-0.0007
$(Long - Run\ Average)$	(0.0009)	(0.0009)	(0.0008)	(0.0008)
Income per Capita		0.012		-0.010
		(0.015)		(0.014)
No. of Observations	47	47	47	47
R-Squared	0.01	0.02	0.002	0.01

Note: The dependent variable is the change in state personal income 10 or 12 quarters after a monetary policy hits the economy. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 3.10: Cross-Section Estimation of Long-Run Inequality Effect–F

	State Private Employment			
	(Q10)	(Q10)	(Q12)	(Q12)
Annual Gini	0.0005	0.0003	0.0002	0.000001
$(Long - Run\ Average)$	(0.0007)	(0.0007)	(0.0007)	0.0007
Income per Capita		0.017		0.015
		(0.012)		(0.012)
No. of Observations	47	47	47	47
R-Squared	0.01	0.007	0.02	0.008

Note: The dependent variable is the change in state private employment 10 or 12 quarters after a monetary policy hits the economy. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 3.11: Cross-Section Estimation of Long-Run Inequality Effect–G

	State Personal Income			
	(Q6)	(Q6)	(Q8)	(Q8)
Top 10% Income	0.00007	-0.0007	0.0001	-0.0008
(Long − Run Average)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Income per Capita		0.047**		0.051***
		(0.019)		(0.017)
No. of Observations	47	47	47	47
R-Squared	0.02	0.09	0.02	0.13

Note: The dependent variable is the change in state personal income six or eight quarters after a monetary policy hits the economy. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 3.12: Cross-Section Estimation of Long-Run Inequality Effect–H

	State Private Employment			
	(Q6)	(Q6)	(Q8)	(Q8)
Top 10% Income	0.0002	-0.0002	0.0004	0.00006
(Long − Run Average)	(0.0004)	(0.0004)	(0.0004)	(0.0005)
Income per Capita		0.025*		0.024*
		(0.013)		(0.013)
No. of Observations	47	47	47	47
R-Squared	0.02	0.05	0.01	0.04

Note: The dependent variable is the change in state private employment six or eight quarters after a monetary policy hits the economy. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

Table 3.13: Cross-Section Estimation of Long-Run Inequality Effect–I

	State Personal Income			
	(Q10)	(Q10)	(Q12)	(Q12)
$Top\ 10\%\ Income$	-0.001*	-0.002**	-0.0009*	-0.0009
$(Long-Run\ Average)$	(0.0005)	(0.0006)	(0.0004)	(0.0006)
$Income\ per\ Capita$		0.029*		0.00005
		(0.016)		(0.015)
No. of Observations	47	47	47	47
R-Squared	0.05	0.10	0.05	0.03

Note: The dependent variable is the change in state personal income 10 or 12 quarters after a monetary policy hits the economy. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

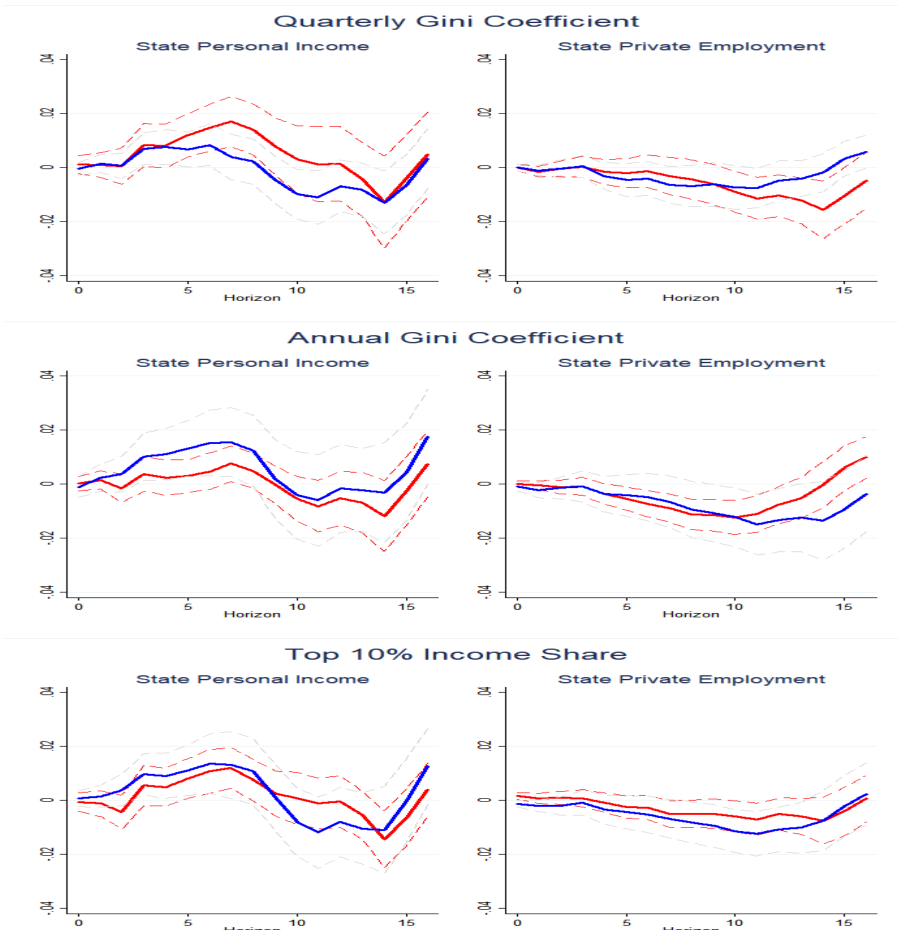
Table 3.14: Cross-Section Estimation of Long-Run Inequality Effect–J

	State Private Employment			
	(Q10)	(Q10)	(Q12)	(Q12)
$Top\ 10\%\ Income$	0.0004	0.00004	0.0002	-0.0001
$(Long-Run\ Average)$	(0.0005)	(0.0005)	(0.0004)	(0.0004)
$Income\ per\ Capita$		0.017		0.017
		(0.014)		(0.014)
No. of Observations	47	47	47	47
R-Squared	0.01	0.003	0.02	0.007

Note: The dependent variable is the change in state private employment 10 or 12 quarters after a monetary policy hits the economy. *: $p < 0.1$, **: $p < 0.05$, ***: $p < 0.01$.

3.8 Appendix C: Monetary Policy Transmission on States with the Highest and Lowest Levels of Income Inequality

Figure 3.6: Monetary Policy Transmission on Top/Bottom 10 States with Highest/Lowest Inequality



Note: Blue line represents the IRF of the five states with higher income inequality. Red line represents the IRF of the five states with lower income inequality. Dashed lines delimit the 95% confidence intervals. X-axes show quarters after the shock. Newey-West standard errors are used. Annual Gini and top 10% income share estimated by M. Frank (2014). Quarterly Gini estimated by Fischer et al. (2021).

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