# Why Are Some Recoveries Weak and Others Strong?

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**Abstract**

Why were the recoveries from the 1990-1, 2001, and 2007-9 recessions weak relative to other postwar recessions? Leveraging heterogeneous exposure to the national business cycle across U.S. States, we estimate the trajectory of more exposed U.S. States relative to less exposed U.S. States. For the 1990-1, 2001, and 2007-9 recessions we estimate that more exposed States experienced a stronger boom-bust cycle and for the other postwar recessions we estimate a deeper V-shaped recession in more exposed States. Our estimates support theories that these recessions are caused by different shocks. In a quantitative model matched to our cross-sectional estimates, boom-bust cycles persistently depress the natural rate of interest $R^*$ in the recovery, whereas $R^*$ is elevated following V-shaped recessions.

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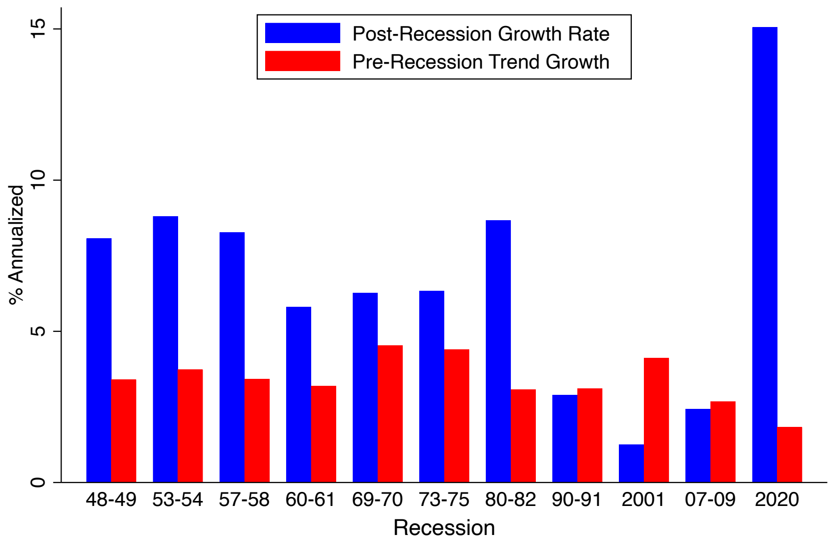
# 1 Introduction

The recoveries from the 1990-1, 2001, and 2007-9 recessions have been weak. The blue bars in Figure 1 show that private domestic demand[1] grows by only 2.2% on average in the four quarters following these recessions, much less than the 8.4% average growth rate in the four quarters following other recessions. The red bars show that growth after each of the 1990-1, 2001, and 2007-9 recessions is also weak relative to the pre-recession trend, computed as the annualized growth rate from the last business cycle peak to the current business cycle peak. This contrasts with the strong recoveries from the other recessions, in which recovery growth exceeds the pre-recession trend. This paper asks why are the recoveries from the 1990-1, 2001, and 2007-9 weak—recovery growth is below the pre-recession trend—and why are recoveries from the other recessions strong?

Figure 1: Growth of Private Domestic Demand after Recession Trough



Note: The post-recession growth rate is the growth rate of private domestic demand (consumption expenditures plus private investment) for the four quarters after the recession trough. The pre-recession trend is the annualized growth rate between the prior business cycle peak and the current business cycle peak, except for 1948-9 where the trend is linearly extrapolated from 1947Q1-1948Q4.

A range of explanations have been put forward to explain why some recoveries are weak: Bad luck (Galí, Smets, and Wouters, 2012), investment boom-bust cycles (Beaudry, Galizia, and Portier, 2018; Rognlie, Shleifer, and Simsek, 2018), credit boom-bust cycles (Jordà,

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[1] The sum of consumption expenditures and private investment.

Schularick, and Taylor, 2013), different sectoral incidences of shocks (Beraja and Wolf, 2022), changes in beliefs (Kozlowski, Veldkamp, and Venkateswaran, 2019, 2020), the secular decline in manufacturing (Leamer, 2021), hysteresis (Benigno and Fornaro, 2018; Garga and Singh, 2021; Reifschneider, Wascher, and Wilcox, 2015), and an exogenous slowdown in trend growth (Fernald, Inklaar, and Ruzic, 2025).

These theories imply different counterfactual paths for output. Figure 2a illustrates these counterfactuals around a hypothetical GDP path similar to the Great Recession. Hysteresis or changes in beliefs due to the recession imply a persistent gap between realized GDP and its counterfactual path absent the recession. An exogenous slowdown in trend growth instead implies that growth would have been weak even absent the recession. We also expect the counterfactual and realized GDP path to converge as bad luck eventually ends. And boom-bust explanations imply that GDP grew faster before the recession than its counterfactual, and through the recession converges to counterfactual GDP.

Distinguishing between these theories is difficult because the counterfactual path of output is unobserved. Common strategies to recover aggregate counterfactuals include extrapolating from existing trends (e.g., Blanchard, Cerutti, and Summers, 2015), extrapolating from other countries or past recessions (e.g., Jordà, Schularick, and Taylor, 2013), or using a structural model to infer shocks and counterfactuals (e.g., Galí, Smets, and Wouters, 2012). That disagreement about the correct counterfactual remains reflects that each of these methods embodies important trade-offs. Trend extrapolation holds fixed the country and the recession, but must assume that the trend continues on its existing path. In practice, trend extrapolations are sensitive to the chosen horizon (Ball, 2015), and would be invalid under some theories such as boom-bust cycles or if aggregate output is non-stationary. In comparing a recession to past recessions or across countries one needs to determine which differences need to be controlled for in order to generate a valid counterfactual (Howard, Martin, and Wilson, 2011). Finally, structural models may imbue the researchers priors, such as over what mechanisms are most important, as well as model misspecification in the analysis (Kehoe, Midrigan, and Pastorino, 2018).

Figure 2b shows that regional data can help uncover the underlying counterfactual. For simplicity, suppose that there are two regions, one is completely exposed and one is completely unexposed to the recession. If the two regions are on parallel trends absent the recession, then the unexposed region provides the correct counterfactual for the exposed region.[2]

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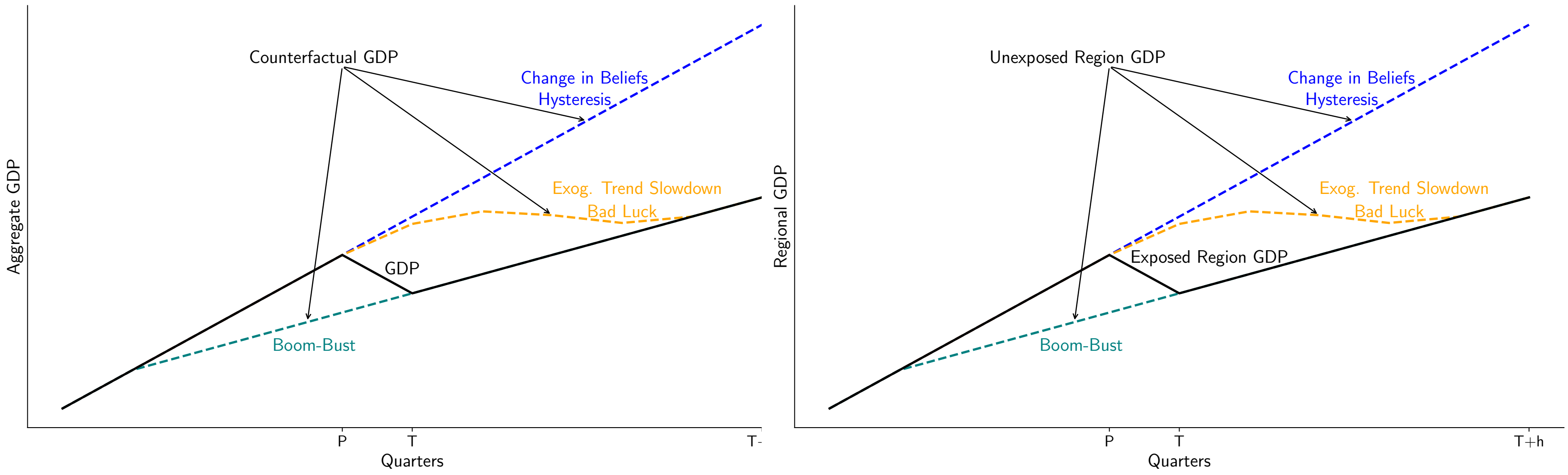
[2] The Figure and discussion abstracts from regional convergence forces, such as migration, because these tend to be slow relative to business cycle frequencies both in our data and in existing work by Blanchard, Katz, Hall, and Eichengreen (1992) and Yagan (2019). Our model in Section 5 accounts for convergence and how they drive a wedge between the regional and the aggregate counterfactual.

Figure 2: Explanations for Weak Recoveries



(a) Aggregate Counterfactuals

(b) Regional Identification

(c) Relative Recession Effects Across Regions

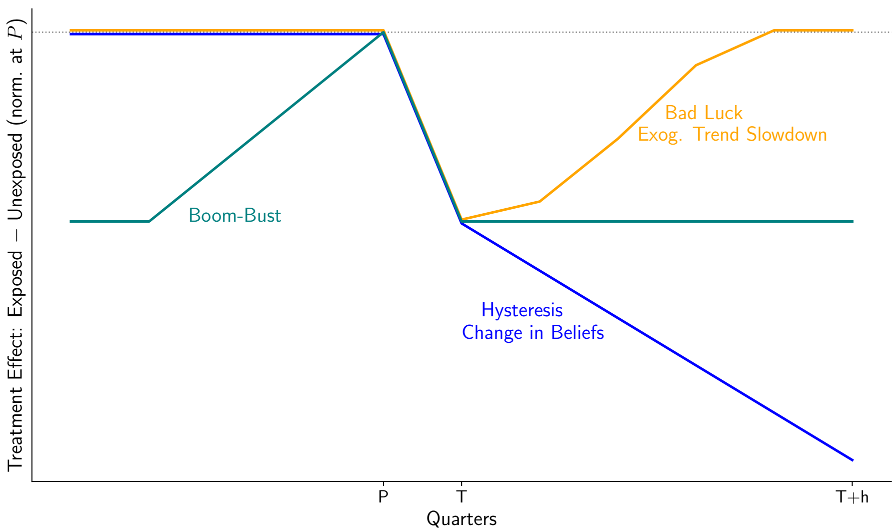


Figure 2c translates the counterfactuals into the relative recession effect across regions: the difference between the exposed and the unexposed region. This object can be interpreted as the relative impulse response function of the recession across regions, which we can estimate directly from the data even when exposure is not binary. The figure shows that the different theories imply different shapes for the relative recession effect. Hysteresis or changes in beliefs imply a persistent negative relative recession effect; an exogenous slowdown in trend growth or bad lack predict a U- or V-shaped impulse response function; and boom-bust cycles imply a positive pre-trend prior to the recession. Thus, we can discriminate between theories for weak recoveries based on the shape of the relative recession impulse response function.

The cross-region approach holds several advantages in estimating the impulse response function of the recession over other methods. First, as aggregate trends are differenced out, it does not require taking a stance on the stationarity of aggregate GDP, which is notoriously difficult to determine (Stock and Watson, 1999). Second, if regions are on different trend trajectories and these are correlated with recession exposure, then differential trends will be directly estimated as part of the impulse response function rather than imposed ex ante. Differential trends sufficiently far in advance of the recession may then be informative about the underlying relative trend, even when the immediate differential trend contains a boom-bust cycle. Third, regional data holds the country and the recession fixed, which reduces the set of possible confounding factors relative to cross-country comparisons. For instance, counterfactuals derived from other countries are likely invalid if their recessions are caused by different types of shocks or are subject to a different monetary policy response. Fourth, the larger sample size in regional data increases statistical power, which helps to identify heterogeneous effects across recessions.

Our empirical approach leverages heterogeneous exposure of U.S. States to the national recession. We construct a Bartik instrument based on State industry shares from the quarterly State personal income accounts at the beginning of all post-war recessions and combine them with detrended national industry growth rates from the NBER recession peak to the NBER recession trough. We instrument local recession depth to estimate how income, employment, unemployment, and GDP trajectories differ across more and less exposed U.S. States around national recessions.

For recessions with a strong national recovery (pre-1990 and 2020), we estimate a deeper V-shape recession in more exposed U.S. States relative to less exposed States. The more exposed States see a larger fall in income, GDP, and employment and a larger increase in unemployment during the recession, but then grow more quickly in the recovery compared to less exposed States. Our estimates are consistent with a complete relative recovery, particularly once accounting for more exposed States growing relatively slowly prior to the recession. This reflects that pre-1990 recession exposure largely correlates with the manufacturing share in State income, and manufacturing is a secularly declining sector.

For recessions with a weak national recovery, 1990-1, 2001, and the Great Recession, we find that more exposed States experience a stronger boom-bust cycle. In the national recovery phase, the more exposed States do not grow faster despite their deeper local recession. However, they do grow more quickly prior to the recession. Thus, the recession displays an inverse V-shape consistent with boom-bust explanations for weak recoveries (Beaudry, Galizia, and Portier, 2018; Jordà, Schularick, and Taylor, 2013; Rognlie, Shleifer, and Simsek, 2018). Going back prior to the pre-recession boom also reveals that the more exposed States were originally on a slower (per capita) growth trajectory compared to the less exposed States. The weak recovery we estimate is consistent with a return to this weaker relative trend.

A corollary of our estimates is that we do not uncover an important role for hysteresis in recessions with either weak or strong aggregate recoveries (Cerra, Fatás, and Saxena, 2023). Our estimates for strong national recoveries support plucking models of the business cycle (Friedman, 1993; Dupraz, Nakamura, and Steinsson, 2023), in which recessions are a drop in output below the balanced growth path. For the weak national recoveries of 1990-1, 2001, and the Great Recession, our evidence for local income and GDP is consistent with an "upward" plucking, in which the recession is a drop from an unsustainable boom. However, the boom has a relatively minor effect on the pre-recession unemployment rate, which suggests that the unemployment rate is unlikely to be an effective diagnostic for a boom-bust cycle.

Following Goldsmith-Pinkham, Sorkin, and Swift (2020) we decompose our impulse response functions into the recession trajectories implied by exposure to a particular sector and the associated sectoral weights. This allows us to test whether changes in the impulse response functions across recessions are due to changes in recession trajectories from particular sectoral exposures or changes in sectoral exposure weights. Across different sectoral exposures, we find evidence of V-shaped recessions in more exposed States for the pre-1990 recessions and COVID-19, and boom-bust cycles for the 1990-1, 2001, and Great Recession. This suggests that changing recovery patterns extend beyond the manufacturing sector emphasized by Leamer (2021). Furthermore, changes in sectoral weights play a minor role in explaining weak versus strong recoveries.

We then show that distinguishing between the two types of recessions that we identify matters for policy. We first show that a two-region New Keynesian model with a durable good can match the different recession patterns in the data. Regions are differentially exposed to a national recession because they specialize in different goods, which allows us to compute cross-regional impulse response functions in the same way as in the data. Boom-bust shocks predict a weak recovery in the model because the output in more exposed regions is inflated at the onset of the recession and will diverge from output in less exposed regions. Shocks that induce intertemporal trade-offs, such as monetary policy or a temporary pandemic, instead predict a strong recovery as the recession is simply a temporary deviation from the balanced growth path.

We use the model to calculate the long-run path of the natural rate of interest $R^*$—the real interest rate that closes the output gap. The model predicts that boom-bust recessions are followed by a prolonged slump in $R^*$, whereas intertemporal shocks raise $R^*$ in the recovery. This follows from the different dynamics of the capital stock: in boom-bust cycles the capital stock is too high and investment too low, so aggregate demand must be supported by a period of prolonged low real interest rates. However, following intertemporal recessions, the capital stock is too low as investment was delayed, which implies that the recovery is supported by pent-up demand. This shows that appropriately calibrating monetary policy in the recovery depends importantly on a correct diagnosis of the recession.

## 2 Empirical Strategy

Our objective is to estimate the effect of a deeper recession in one U.S. State relative to another on the subsequent relative recovery in the two States. We use the following specification:

$$y_{i,T_j+h} - y_{i,P_j} = \alpha_{j,h} + \beta_h(\hat{y}_{i,P_j} - \hat{y}_{i,T_j}) + \varepsilon_{i,j,h} \tag{1}$$

Here $y_{it}$ is the outcome for U.S. State $i$ at time $t$ (e.g., income, employment, or GDP), $\hat{y}_{it}$ its deviation from a prior trend, $j$ denotes a national recession with associated NBER peak date $P_j$ and trough date $T_j$ (measured quarterly), and $h$ denotes the horizon relative to the NBER trough. $\alpha_{j,h}$ is a set of recession-horizon fixed effects and $\varepsilon_{i,j,h}$ denotes other unmodelled influences on the outcome variable.

The outcome variable $y_{i,T_j+h} - y_{i,P_j}$ measures the growth relative to the NBER recession peak in State $i$. $h = 0$ corresponds to the change in the outcome over the recession. The independent variable $\hat{y}_{i,P_j} - \hat{y}_{i,T_j}$ is the recession depth in State $i$ relative to trend. When there is no trend, we would obtain $\beta_0 = -1$ by construction. For $h \neq 0$, the parameter $\beta_h$ captures what proportion of the original recession depth (relative to trend) remains after $h$ quarters. For example, if we estimate a recession elasticity $\beta_h = 0$ for some $h > 0$, then the relative growth from the NBER peak is completely unrelated to the recession depth that a State experienced. That is, the subsequent recovery has exactly compensated for any relative difference in recession depth. If instead $\beta_h = -1$ for $h > 0$ then the U.S. State that experienced a deeper recession has experienced no catch-up relative to a State that experienced a shallower recession.

Common components to State growth, such as aggregate TFP growth, are absorbed by the recession-horizon fixed effect $\alpha_{j,h}$. This yields three important advantages over extrapolating from existing aggregate trends (e.g., Blanchard, Cerutti, and Summers, 2015). First, our approach is not sensitive to the stationarity properties of aggregate TFP or aggregate output. Second, we do not need to take a stance on which time period to calculate the aggregate trend. Ball (2015) shows that trend extrapolation is sensitive to this choice. And third, we do not assume that the evolution of aggregate output prior to the recession is independent of the recession itself, which would be incorrect if recessions were due to boom-bust cycles.

The identification problem is to separate the local effects of the national recession from the error term $\varepsilon_{i,j,h}$, which contains any local shocks to State growth, measurement error, and differences in trends. Standard OLS estimates of $\beta_h$ are likely biased. For example, a positive State-specific shock during the recession, such as the relocation of a large firm or a positive labor supply shock, would reduce both the local recession depth and increase the magnitude of the recovery biasing $\beta_h$ downward. On the other hand, measurement error in the local recession depth, e.g., from mismeasurement in local trends or misalignment of the national recession dates with the local cycle, would bias $\beta_h$ towards zero. The identification problem is reminiscent of panel approaches, which must assume that country-specific shocks are uncorrelated with recession intensity.

To address the identification problem, we instrument for local recession depth using a Bartik instrument. For each State we construct the Bartik predicted recession depth based on the local industry composition and national industry growth relative to trend. Let $s_{ikt}$ be the income share of industry $k$ in state $i$ at time $t$. Let $\hat{g}_{-i,k,t,t+m}$ be the detrended national growth rate of industry $k$ excluding state $i$ from $t$ to $t+m$. The Bartik predicted recession depth is then,

$$\hat{y}^b_{i,P_j} - \hat{y}^b_{i,T_j} = \sum_{k=1}^{K} s_{i,k,P_j} \hat{g}_{-i,k,T_j,P_j}. \tag{2}$$

The Bartik instrument exploits differential exposure of States to the national recession based on the local industry composition. In order to be a valid instrument, this exposure must be uncorrelated with other local shocks that affect recession and recovery dynamics $\varepsilon_{i,j,h}$ conditional on controls. Following the previous examples, we require that State-specific shocks and measurement error are not systematically more positive or negative in more exposed States.

An advantage of the regional Bartik approach is that it uses the variation of interest by comparing regions that are more or less exposed to the same national recession. This is important if recessions vary in their effect on output $\beta_h$. By holding the recession and country fixed, including the monetary policy reaction, the Bartik instrument is informative about the local average treatment effect. In contrast, the cross-country panel approach must assume that the effects of recessions are homogeneous across countries, despite potentially different shocks and fiscal and monetary reaction functions.

The Bartik instrument will load on differences in State trend growth to the extent that these are correlated with recession exposure. If differences in trend are due to the recession, e.g., in boom-bust cycles or due to hysteresis, this is necessary to uncover the correct recession effect. Our regression model (1) therefore imposes no restrictions on either pre-recession or post-recession relative trends.

However, as a consequence, our estimates for $\beta_h$ will also incorporate long-term differences in trend that are orthogonal to the recession itself. For instance, States with a relatively large manufacturing base tend to be more sensitive to the business cycle and have also been secularly declining. We identify these relative trends in two ways. First, by estimating $\beta_h$ sufficiently far in advance of the recession such that it is not affected by a potential boom-bust cycle. This strategy is valid under all theories of weak recovery, so long as $h$ is sufficiently negative. Second, we use the $\beta_h$ for unemployment to determine at what point the economy is at similar point in the business cycle. As shown by Blanchard, Katz, Hall, and Eichengreen (1992) and Yagan (2019), unemployment converges across regions even when other variables do not, which makes it suitable for isolating their relative trends from the business cycle.

**2.1 Data** Our identification strategy requires business-cycle frequency data that is disaggregated by both location and industry for the entire post-war period. We use the quarterly BEA State personal income data, which is disaggregated by industry since 1948. The industry detail increases from 12 SIC sectors from 1948-57 to 14 SIC sectors from 1957-2001 and to 24 NAICS sectors from 1997 onward. Our outcomes are quarterly State personal income, quarterly State unemployment rates from Fieldhouse, Munro, Koch, and Howard (2024), quarterly State employment data from the BLS,[3] and, post-2005, quarterly State-level GDP from the BEA. We deflate all nominal variables using the national GDP deflator, and convert all data (except unemployment) to per capita using State population estimates from the U.S.

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[3] We seasonally adjust the raw monthly employment data using the Census X-13 algorithm up to February 2020. We then apply the last year of seasonal factors to the remaining sample. This procedure avoids contamination of the seasonal factors by the sharp Covid recession. We then aggregate the seasonally adjusted data to a quarterly frequency.

Census linearly interpolated to a quarterly frequency.

When using personal income data we aim to closely proxy for local private output. We therefore exclude the government sector from personal income. We also exclude the finance, insurance, and real estate (FIRE) sector and agriculture and mining. For these sectors we find the largest divergence between local GDP growth and local personal income growth, likely because the geography of ownership and production are more often different in these sectors than in other sectors.

We follow the standard NBER dating for recession peaks and troughs, except that we combine the 1980 and 1981-2 recession into a single episode. We detrend both State recession depth and national industry growth using NBER-peak to NBER-peak growth rates. This gives us (1) a slightly stronger first stage and (2) puts more weight on sectors that experience a sharp change in growth rates in a recession relative to sectors that grow fast or slow due to an underlying trend. For the 1948-9 recession and for the SIC-NAICS switch in 1997 we do not have industry data from the prior peak, in which case we proxy the trend using the average growth rate from the available data up to the current peak.[4]

## 3 Illustration of the Empirical Approach

Goldsmith-Pinkham, Sorkin, and Swift (2020) show that estimation using the Bartik instrument (2) is equivalent to weighted GMM using the shares $s_{i,k,P_j}$ as instruments.[5] We therefore illustrate the empirical approach based on the sectoral shares that receive the highest weight in the Bartik instrument. Specifically, in Section 4.4 we show that the Bartik instrument loads most strongly on the manufacturing share in pre-1990 recessions, on the construction share in the Great Recession, on the accommodation and food sector during COVID-19, and on IT and professional services in the 2001 recession.

Figure 3 plots the time path of average per-capita State personal income relative to the national recession peak, when sorted by the key sources of variation in the Bartik instrument. The top left panel sorts U.S. States by their manufacturing share in each recession, and then pools across all pre-1990 recessions.[6] The average recession begins five quarters before the trough, when the high and low manufacturing groups cross at 0 on the y-axis. The difference between the two groups at the NBER trough (0 on the x-axis) therefore measures the relative

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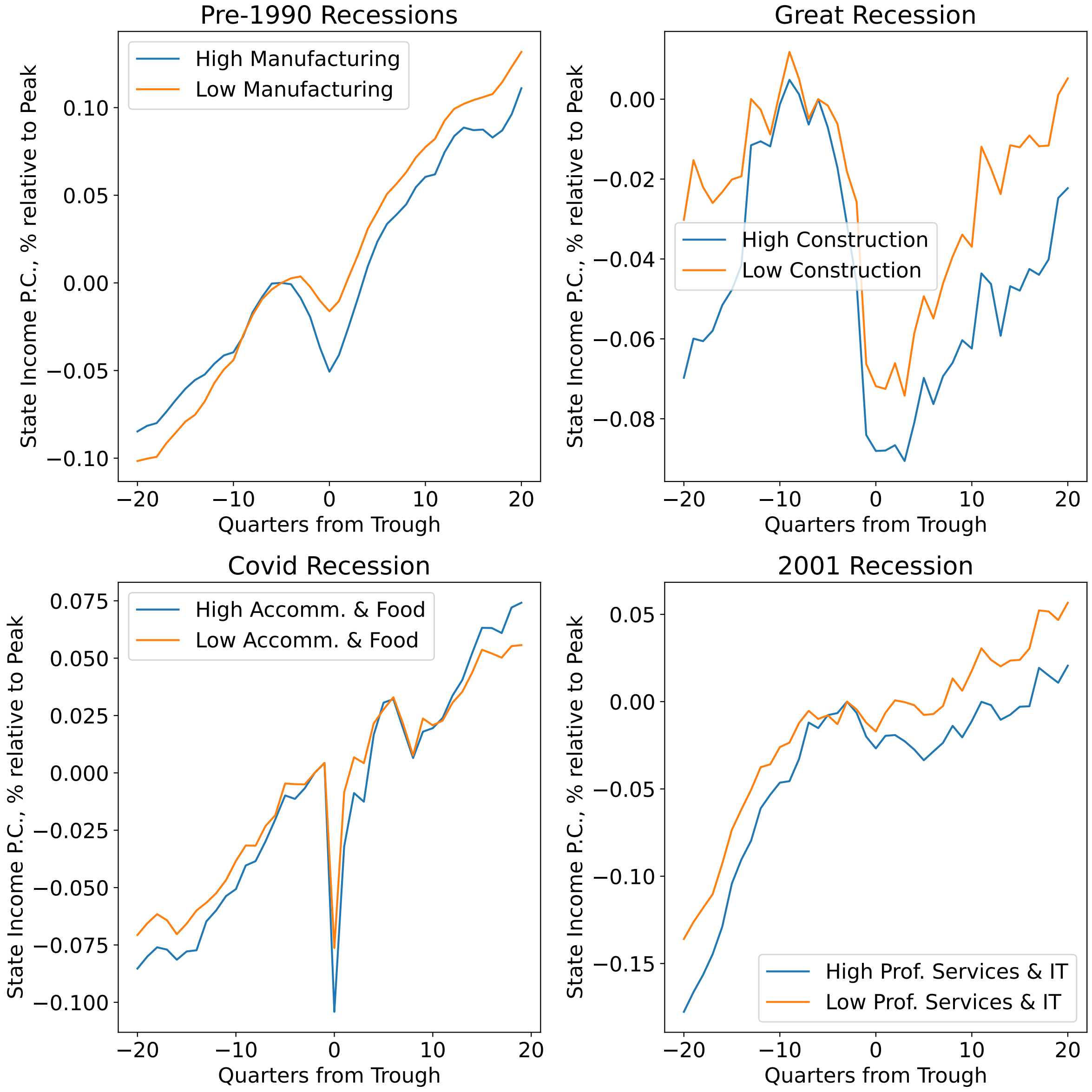
[4] The Personal Income files switch to a more detailed SIC classification in 1957. We aggregate these to the coarser historical classification for the purpose of constructing peak-to-peak growth rates for the 1957-8 recession.

[5] Adao, Kolesár, and Morales (2019) and Borusyak, Hull, and Jaravel (2022) also show that identification is also possible based on exogeneity of the sectoral shocks rather than the sectoral shares. However, their approach requires a large number of independent sectoral shocks, which is not applicable to our setting.

[6] We group States on whether they are above or below the mean share separately for each recession.



Pre-1990 Recessions

Great Recession

Covid Recession

2001 Recession

Figure 3: Outcomes by Key Sources of Variation of the Bartik Instrument

recession depth. The high manufacturing States decline by 3.4% more during the recessions relative to the low manufacturing States. In other words, the high manufacturing States are more exposed to the national recession.

After the recession trough, high manufacturing areas grow more quickly than low manufacturing areas, which indicates that they catch up from a deeper recession. The high manufacturing areas grow an additional 1.8% in the ten quarters of the recovery, making up more than half of the relative recession depth. The top left panel also shows that high-manufacturing States grow 0.11% less per quarter relative to low-manufacturing States before the recession. Accounting for this relative trend implies that the relative recovery is complete after 10 quarters.[7]

The pre-1990 recession plot also illustrates that our cross-sectional recession elasticities are robust to misspecification of the aggregate trend, unlike a time-series analysis. Both the low and high manufacturing areas are 2.4% below their pre-recession trend 10 quarters after the recession trough. But this may reflect that the aggregate pre-recession trend was too high for both groups. Blanchard, Cerutti, and Summers (2015) show that time-series estimates of output gaps are very sensitive to assumptions about the aggregate pre-recession trend. Our analysis does not require taking a stance on the aggregate pre-recession trend.

In the top right panel of Figure 3 we show that U.S. States loading more on the construction sector in the Great Recession experience both a deeper recession and a weaker recovery. Specifically, high construction exposure predicts a 1.6% deeper recession and a 0.9% weaker recovery in the first ten quarters after the NBER trough. These patterns are very different from the pre-1990 recession, in which more exposed States were catching up after the recession. Another difference is the pre-trend: The more exposed States in the Great Recession grew faster than the less exposed States. These patterns inform our cross-sectional regression that the Great Recession was a boom-bust cycle.

The COVID-19 recession shows a similar pattern to the pre-1990 recessions: States with a steeper recession due to greater exposure to accommodation and food also experience stronger recoveries. The catch-up in levels is nearly complete: the recession is 2.8% deeper in the States with a high accommodation and food share, but the recovery is also 2.6% stronger.

The final subplot on the bottom right shows that for the 2001 recession the patterns are qualitatively similar to the Great Recession: a deeper recession due to a greater loading on IT and professional services implies a weaker recovery. More exposed States also grow more quickly before the recession, again indicating boom-bust dynamics across States.

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[7] The relative recovery adjusting for the trend is 1.8% + 15*0.11% = 3.4%, which is equal to the 3.4% relative recession depth.

In summary, the data suggests that the pre-1990 and the Covid recessions have V-shaped recessions in the cross-section, in which a deeper recession predicts a stronger recovery. In contrast, exposure to the Great Recession and the 2001 recession predicts an inverse-V shaped recession: faster growth prior to the recession, followed by a steeper decline and weaker recovery. We next make this finding explicit using regression analysis.

# 4 Results

**4.1 Main Estimates of Recession Counterfactual** We pool our estimates across the two recession groups: those with weak aggregate recoveries (1990-1, 2001, and 2007-9) and those with strong aggregate recoveries (1948-9, 1953-4, 1957-8, 1960-1, 1969-70, 1973-5, 1980-2, 2020). Pooling helps to statistically distinguish these recession groups and is supported by the similar qualitative recession pattern we document above.

We start with the pooled first stage,

$$\begin{aligned}\hat{y}_{i,P_j} - \hat{y}_{i,T_j} = {} & \gamma_1(\hat{y}^b_{i,P_j} - \hat{y}^b_{i,T_j}) I(P_j \in \{1990\text{Q}3, 2001\text{Q}1, 2007\text{Q}4\}) \\ & + \gamma_2(\hat{y}^b_{i,P_j} - \hat{y}^b_{i,T_j}) I(P_j \in \{\text{Other Recessions}\}) + \theta_j + \varepsilon_{i,j,h}\end{aligned}$$

in which we regress recession depth relative to trend $\hat{y}_{i,P_j} - \hat{y}_{i,T_j}$ on Bartik-predicted recession depth $\hat{y}^b_{i,P_j} - \hat{y}^b_{i,T_j}$. We allow the relationship to vary across recession groups. $\gamma_1$ is the elasticity of actual recession depth w.r.t. predicted recession depth in the 1990-1, 2001, and 2007-9 recessions. $\gamma_2$ captures the average elasticity for the other recessions. We control for recession fixed effects $\theta_j$ to isolate within-recession variation. Within each Recession Group we cluster by State.[8]

The pooled first stage estimates are shown in Table 1. In columns (1) and (2) we show that predicted recession depth based on State income shares and national trends strongly predicts State recession depth in income. For the 1990-1, 2001, and 2007-9 recessions the first stage coefficient for income included in the instrument is $\gamma_1 = 3$ (t-statistic 4.3). This means that a 1% deeper predicted recession translates into a 3% deeper local recession. For the other recessions the first stage coefficient is $\gamma_2 = 1.4$ (t-statistic 5.1). In columns (3) through (5) we measure State recession depth relative to trend with the unemployment rate, employment, and GDP. In each case, our Bartik instrument is a powerful predictor of the State recession depth.

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[8] Double-clustering by both State and recession date and adjusting for small numbers of clusters following Imbens and Kolesar (2016) generally produces smaller standard errors than clustering by State alone. See Figure 10. This suggests that our Bartik approach largely captures cross-state correlations, consistent with Adao, Kolesár, and Morales (2019).

Table 1: First Stage of Local Recession Depth on Predicted Recession Depth

| Local Recession Depth: | Incl. Earnings | All Earnings | Unempl. | Empl. | GDP |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| *Coeff. on Predicted Recession Depth*: | | | | | |
| 90-1, 01, 07-9 Recessions | $3.11^{***}$ | $2.49^{***}$ | $-54.7^{**}$ | $1.91^{***}$ | $5.66^{***}$ |
| | (0.71) | (0.67) | (26.9) | (0.37) | (0.85) |
| Other Recessions | $1.42^{***}$ | $0.67^{***}$ | $-64.6^{***}$ | $0.79^{***}$ | $0.85^{***}$ |
| | (0.28) | (0.22) | (9.08) | (0.19) | (0.28) |
| Recession FE | Yes | Yes | Yes | Yes | Yes |
| F-Statistic 90-1, 2001, 07-9 | 19.0 | 13.9 | 4.1 | 26.2 | 44.3 |
| F-Statistic Other Rec. | 25.8 | 8.9 | 50.6 | 17.5 | 9.3 |
| State Clusters | 100 | 100 | 100 | 100 | |
| $R^2$ | 0.36 | 0.28 | 0.60 | 0.57 | 0.42 |
| Observations | 544 | 544 | 541 | 541 | 100 |

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

**4.2 Impulse Response Functions** We next estimate relative recession impulse response functions across recession groups. Within each group, these capture the differential movement of income across more and less exposed States both before and after the national recession.

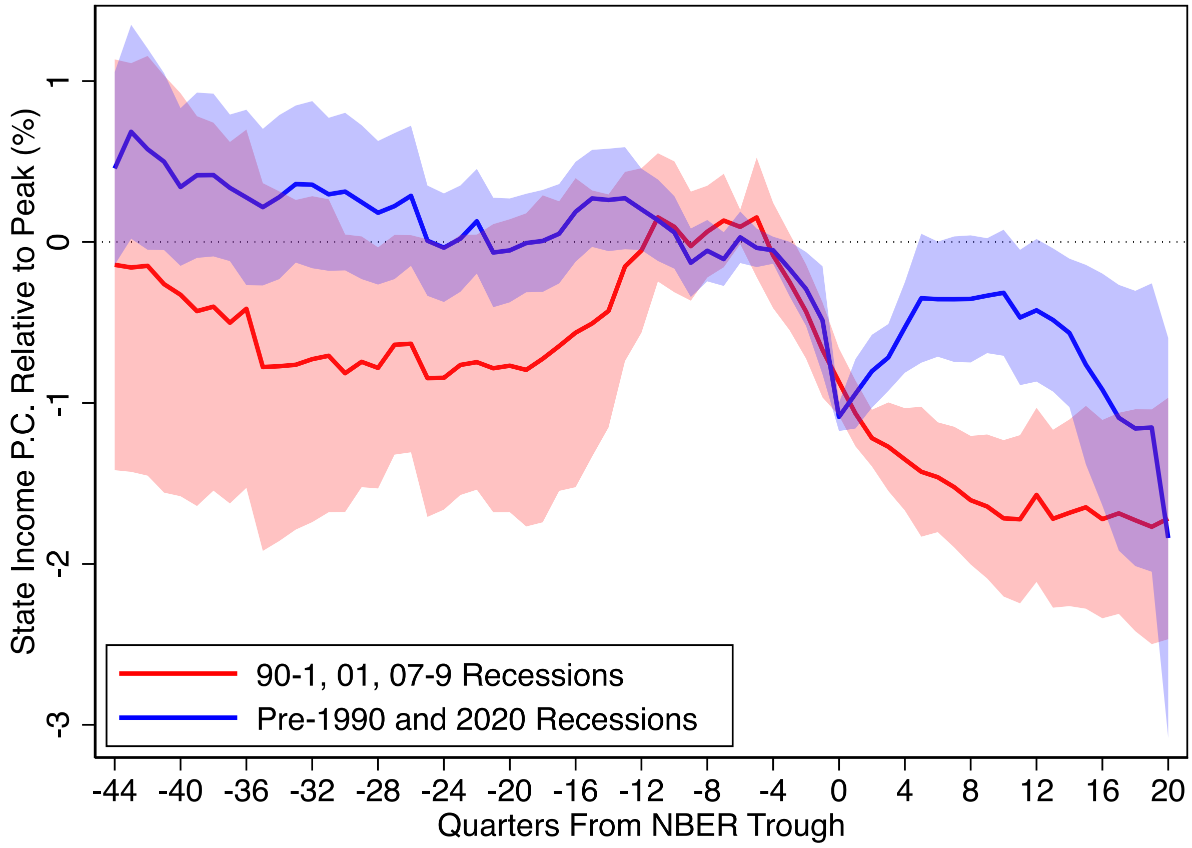
Specifically, we pool equation (1) across recession groups,

$$\begin{aligned} y_{i,T_j+h} - y_{i,P_j} = {} & \beta_{1h}(\hat{y}_{i,P_j} - \hat{y}_{i,T_j}) I(P_j \in \{1990\text{Q}3, 2001\text{Q}1, 2007\text{Q}4\}) \\ & + \beta_{2h}(\hat{y}_{i,P_j} - \hat{y}_{i,T_j}) I(P_j \in \{\text{Other Recessions}\}) + \alpha_{j,h} + \varepsilon_{i,j,h} \end{aligned} \tag{3}$$

where $y_{i,T_j+h} - y_{i,P_j}$ is $h$-quarter growth in the outcome variable since the recession peak $P_j$. We instrument recession depth relative to trend $(\hat{y}_{i,P_j} - \hat{y}_{i,T_j})$ with predicted recession depth relative to trend $(\hat{y}^b_{i,P_j} - \hat{y}^b_{i,T_j})$ (both interacted with the recession group indicators). The parameters $\beta_{1h}$ and $\beta_{2h}$ measure the differential trajectory for a State with a 1% deeper recession compared to another State $h$ quarters after the national recession trough. Since $h$ can be negative we use the same regression to estimate differences in the pre-recession trend. $\beta_{1h}$ captures the differential trajectories for the 1990-1, 2001, and 2007-9 recessions and $\beta_{2h}$ for the other recessions.

Figure 4 plots our estimates $\beta_{1h}$ and $\beta_{2h}$ for $h = -44$ quarters before the recession trough to $h = 20$ quarters after the recession trough. For $h = 0$, the estimate is close to -1 for both recession groups. If there were no trends in our measure of local recession depth, these

Figure 4: Impulse Response Function of State Personal Income P.C. by Recession Group



estimates would be equal to -1 exactly. They are close to -1 because the relative trends are not very important over the short recession duration.

Other than the immediate period prior to the recession trough $h = 0$, the two recession groups look different. For the 1990-1, 2001, and 2007-9 recessions, a deeper relative recession predicts a weaker relative recovery. This is reflected in the decreasing estimates of the relative recession effect for $h > 0$. Thus, States that are more exposed to the recession experience relatively weaker growth in the recovery compared to less exposed States.

From $h = -20$ to $h = -10$, the more exposed States grow relatively more quickly compared to the less exposed States in the 1990-1, 2001, and 2007-9 recessions. This is captured by the increase in $\beta_{1h}$ over this window from roughly -1 to slightly above 0. The strong relative growth in more exposed States is a break from their prior behavior. Going from $h = -20$ back as far as $h - 44$, the more exposed States are growing at either the same or a slightly slower pace than the less exposed States. Our estimates for the recovery are consistent with a return to the slower relative trend five years before the recession trough.

The impulse response functions we estimate for the 1990-1, 2001, and 2007-9 recessions are consistent with the boom-bust cycle based explanations for weak recoveries (Beaudry, Galizia, and Portier, 2018; Jordà, Schularick, and Taylor, 2013; Rognlie, Shleifer, and Simsek, 2018). Comparing our estimates with Figure 2c shows that they are not consistent with bad luck or an exogenous trend slowdown, because we do not see regional convergence after the recession. They are also not consistent with an important role for hysteresis, because we estimate a pre-recession boom and the return to the pre-boom trend.

In contrast, the more exposed States in the pre-1990 and 2020 recessions grow relatively more quickly in the recovery, which is captured by the increasing estimates $\beta_{2h}$ for $h > 0$. Five quarters after the national recession trough, $\beta_{2h}$ is close to, and statistically indistinguishable from, zero. A zero effect implies that any deeper local recession was subsequently made up for by a stronger recovery.[9] The argument for a complete recovery is stronger once we account for the downward relative trend of more exposed States prior to the recession. For the pre-1990 and 2020 recessions the average relative trend is continuously downward and does not display a break.

In summary, the more exposed States to national recessions pre-1990 and 2020 experience a more pronounced V-shape recession followed by a recovery relative to trend. This pattern is consistent with plucking models of the business cycle (Friedman, 1993; Dupraz, Nakamura, and Steinsson, 2023). The fact that we find no evidence for boom-bust cycles for these recessions suggests that the pre-1990 and 2020 recessions and the 1990-1, 2001, and 2007-9

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[9] The subsequent decline for $h > 12$ quarters reflects a subsequent recession: the peak of the 1960-1 recession follows only eleven quarters after the 1957-8 recession.

recessions are caused by different types of shocks.

**4.3 Other Outcomes** Our baseline outcome variable is State income, specifically the components of State income that were included in our Bartik instrument. We next show impulse response functions for four alternative outcomes: all State income (including all sectors, transfers, dividends, and rent), the State unemployment rate, State employment, and for the last two recessions, State GDP. The four impulse response functions are plotted in 5. The first stage for these other outcomes is shown in Table 1.

The boom-bust pattern for all State income in the 1990-1, 2001, and 2007-9 recessions is essentially the same as in our baseline estimates, though less precisely estimated (Figure 5a). For the pre-1990 and 2020 recessions, the recovery appears to be more complete based on all income, but the relative downward trend in more exposed States prior to the recession is also less apparent.

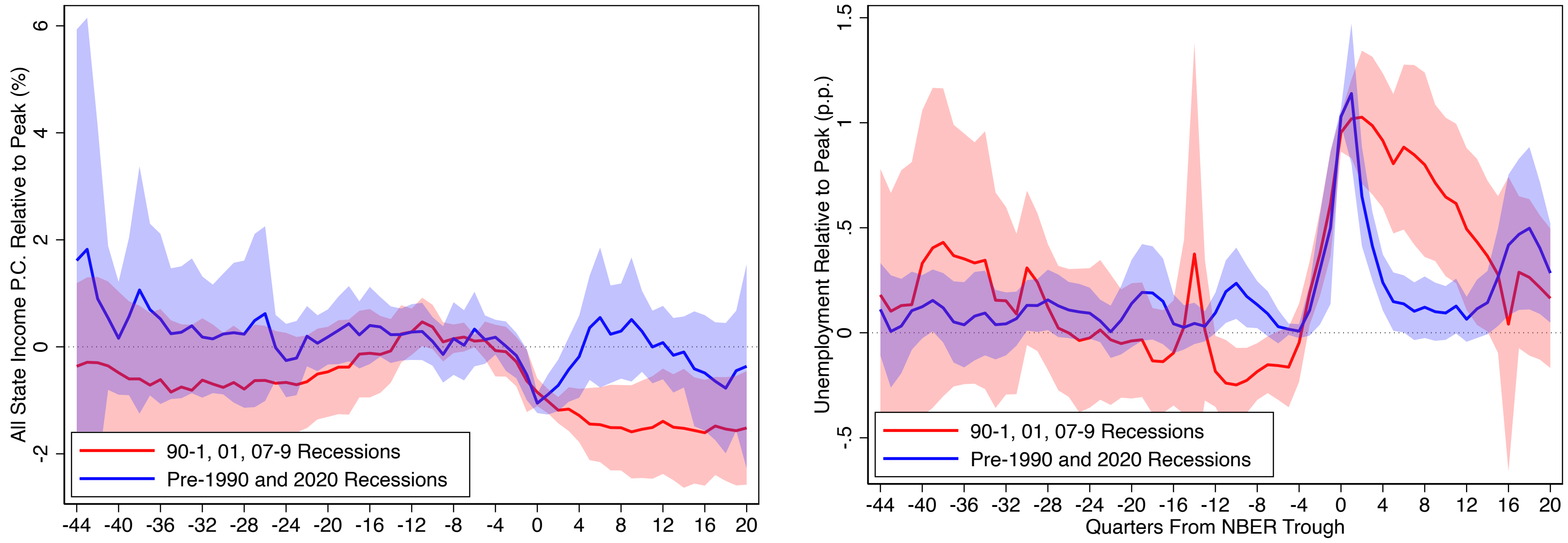
The unemployment impulse response function in Figure 5b is noticeably different from the other outcomes. It displays convergence in unemployment rates across States for all recessions, consistent with prior work by Blanchard, Katz, Hall, and Eichengreen (1992) and Yagan (2019). But the speed is very different: For the 1990-1, 2001, and 2007-9 recessions convergence takes four years, whereas for the pre-1990 and 2020 recessions convergence is almost complete after one year.

There are no noticeable pre-trends in unemployment for the pre-1990 and 2020 recessions. This is consistent with our interpretation that the relative downward trend in State income for more exposed States (Figure 4) reflects structural rather than cyclical forces.

In contrast, unemployment in more exposed States was relatively low at the peak of the 1990-1, 2001, and 2007-9 recessions, consistent with a relative boom in the labor market. However, this boom is small. The boom in State income in Figure 4 in the five years prior to the recession is almost as large as the bust. The decline in unemployment in the five years prior to the recession is only one-fifth as large as the subsequent increase in unemployment. This suggests that boom-bust cycles may have asymmetric effects on labor markets and that unemployment rates are less informative about the boom-bust nature of a recession.

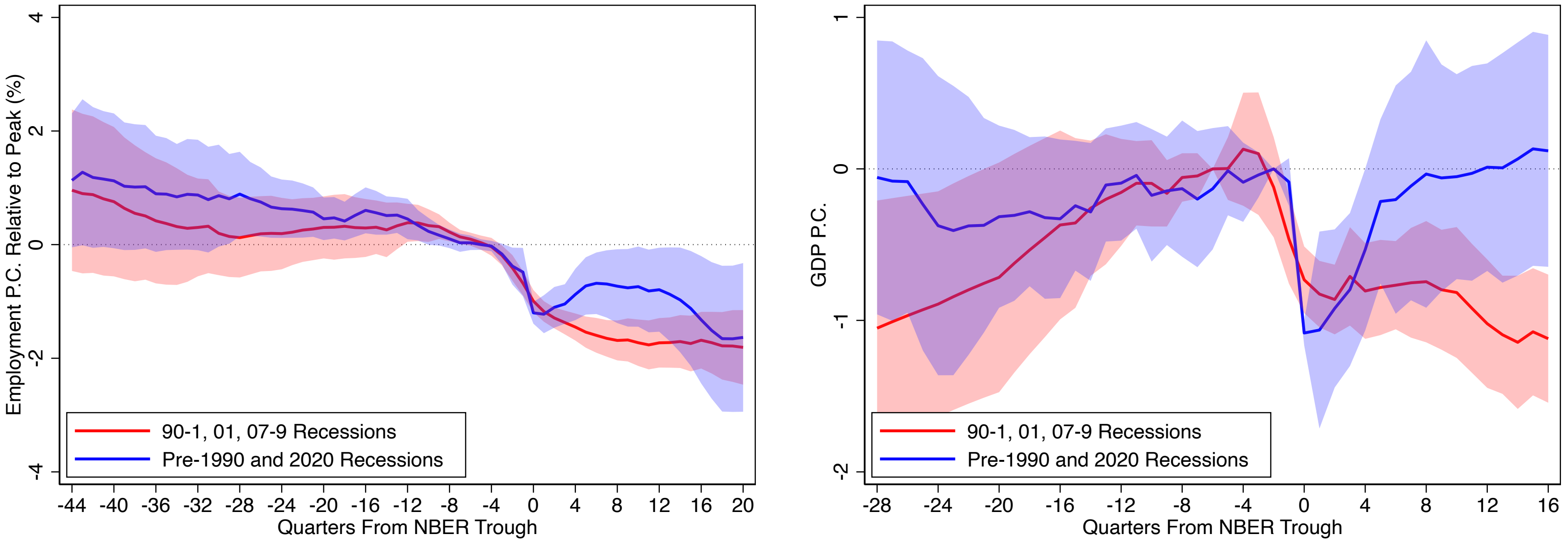
From $h = -44$ to $h = -20$ relative unemployment is relatively flat or slightly decreasing, suggesting that the length of this period is informative about the relative structural trend for the more exposed States in the 1990-1, 2001, and 2007-9 recessions. This points to a relative downward trend in the more exposed States based on both State income and (see below) employment.

Figure 5: Recession Impulse Response Function for Other Outcomes



(a) All State Income P.C.

(b) Unemployment Rate



(c) Employment P.C.

(d) GDP P.C.

Figure 5c shows that more exposed States experience a much stronger relative decline in employment relative to population. The boom prior to the 1990-1, 2001, and 2007-9 recessions barely turns this trend positive. What looks like a level downward-shift in employment after the recession is consistent with a return to the pre-boom trend.[10] For the pre-1990 and 2020 recessions, the downward trend in employment is particularly noticable. Nevertheless, the recovery is V-shaped and employment quickly returns to its pre-recession trend.

The GDP data is more limited since it is only available for the last two business cycles. Yet the patterns are similar to the broader sample for State income. The Covid recession displays a fast recovery to the pre-recession trend. The Great Recession shows a boom-bust cycle. These outcomes corroborate our findings using State income.

For comparison, we plot the relative growth rates of population for the two recession group in Appendix Figure 11. Population grows relatively more in the more exposed States in the 1990-1, 2001, and 2007-9 recessions, but relatively less in the other recessions. Population growth remains smooth throughout the recession, unlike the economic outcomes in Figures 4 and 5. Our results extend the findings of Autor, Dorn, and Hanson (2021) for the Great Recession and support their conclusion that the "estimates for population belie the expectation of a lasting downturn in the CZs with greater exposure to the Great Recession."

**4.4 Decomposition of the Impulse Response Function** We decompose our Bartik estimates to (1) show what variation is most important and (2) determine whether the changes across recessions come from different behavior within or across industries (or both). Goldsmith-Pinkham, Sorkin, and Swift (2020) show that the Bartik estimator is equivalent to a weighted GMM estimator, in which the local industry shares $s_{i,k,P_j}$ in (2) are the instruments and industry growth rates $\hat{g}_{-i,k,P_j,T_j}$ are the weights. When the industry growth rates are common across locations, then we can decompose the Bartik estimate for $\beta_h$ in (1) as

$$\beta_h = \sum_{k,j} \alpha_{k,P_j} \beta_{h,k,P_j}$$

where $\beta_{h,k,P_j}$ is the estimate for $\beta_h$ from instrumenting (1) using the industry share $s_{i,k,P_j}$ and $\alpha_{k,P_j}$ is its associated "Rotemberg" weight in the Bartik instrument. In our setting,

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[10] Yagan (2019) performs a different exercise by projecting the local employment to population ratio on the local unemployment increase over the recession. This regression in our data also shows no pre-trend over 2003-7, but a pre-trend prior to 2003. Furthermore, projecting the local employment to population ratio on the local decline in the employment to population ratio shows a boom period prior to the recession. This suggests that an analysis of pre-trends for the Great Recession depends importantly on the horizon and the variation used.

this decomposition holds only asymptotically since we use leave-one-out growth rates to construct the Bartik instrument. In practice, the estimates from the leave-one-out Bartik and the common growth rate Bartik are very close, so the decomposition remains informative about what sources of variation matter for our estimates.

We focus on the estimates for State income from Figure 4. In Figures 6a and 6b we show how these impulse response functions are informed by exposure to five broad sectoral aggregates that we can consistently define throughout the sample: Construction, manufacturing, transportation and utilities, wholesale and retail trade, and other services. Each estimated impulse response function uses the corresponding local income share of that sector as instrument for local recession depth. When a sector share is largely uninformative about local recession depth, then its corresponding Rotemberg weight $\alpha_{k,P_j}$ will be small and the standard error for $\beta_{h,k,P_j}$ will be large. We therefore exclude sectors with a weight less than 0.05 from the figure. Appendix Figure 12 includes all sectors.

The three major sectors that inform recession depth in the 1990-1, 2001, and 2007-9 recession are construction ($\alpha = 0.28$), transportation and utilities ($\alpha = 0.06$), and other services ($\alpha = 0.59$). Figure 6a shows that recession exposure based on each of these major sectors predicts a boom-bust cycle. In almost all cases, the pooled estimate is within the 95% confidence band of each of the sectoral exposures. Thus, the boom-bust nature of these recessions is broad-based rather than confined to a particular industry. It also suggests that the boom-bust cycle is unlikely to be due to a correlation of sectoral exposure and local income shocks, as one then would expect the boom-bust cycle to be confined to sectors that are overrepresented in locations subject to those local shocks.

Leamer (2021) argues that weak recoveries in the manufacturing sector help explain weak aggregate recoveries in the 1990-1, 2001, and 2007-9 recessions based on cross-State data. While we also find that manufacturing exposure predicts weaker recoveries in the 1990-1, 2001, and 2007-9 recessions, exposure based on the other sectors yields the same pattern. Furthermore, these other sectors matter more both in the cross-section and in the aggregate, based on their Rotemberg weights and aggregate sectoral shares. This suggests that an explanation for weaker recoveries based solely on the changing behavior of manufacturing is likely incomplete.

For the national recessions before 1990 and in 2020, exposure is primarily determined by the local income shares in manufacturing ($\alpha = 0.54$), wholesale and retail trade ($\alpha = 0.09$), and other services ($\alpha = 0.37$). Figure 6b shows that each of the three sectoral exposures predicts a rapid recovery from the NBER trough in these recessions. There is no evidence of boom-bust cycles. If anything, the more exposed States based on manufacturing and wholesale and retail trade are on a downward-trend relative to less exposed States. The recovery from the recession is consistent with a return to this downward-trend. Service sector exposure predicts no differential trend prior to the recession and a complete recovery thereafter.

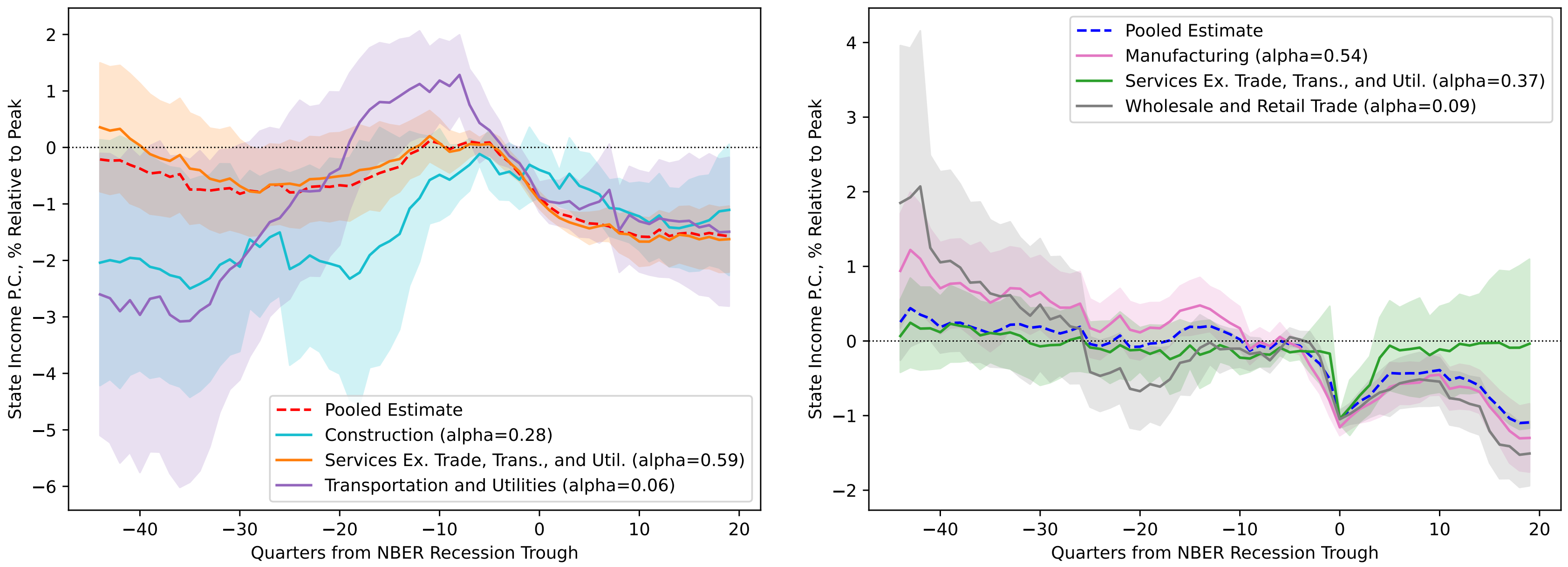
Comparing Figures 6a and 6b, we find that all major sector exposures predict weak recoveries in the 1990-1, 2001, and 2007-9 recessions and strong recoveries in the other recessions. This implies that the weaker recovery dynamics are coming primarily from within-sector changes rather than changes in sectoral weights.

Figures 6c and 6d show the impulse response functions when the variation is restricted to particular recessions. For both the 2001 and 2007-9 recession the boom-bust pattern is evident and each contains the pooled estimate within their 95% confidence bands. This is despite these recessions loading on different sectors. Cross-State variation in recession depth during the Great Recession is best explained using exposure to the construction and health sectors. For the 2001 recession, exposure to health and information and professional services matters most. The Figure omits the 1990-1 recession in which local industry shares have little predictive power for local recession depth, which is reflected in both a low Rotemberg weight $\alpha = 0.02$ and wide confidence band (Appendix Figure 12c).

There is no evidence of a boom-bust cycle in the pre-1990 or the Covid recessions in Figure 6d. Instead, these recessions show a rapid recovery in the quarters after the NBER trough. States more exposed to the 2020 recession show a complete relative recovery within a year to their pre-recession relative trend. This pattern is primarily informed by exposure to the accommodation and food and the entertainment sectors: States like Nevada and Hawaii contracted sharply during Covid but then rapidly recovered as the economy re-opened. The more exposed States to pre-1990 recessions also grow relatively quickly after the recession trough. In this sense, the pre-1990 recessions look similar to the Covid recession and different from the 1990-1, 2001, and 2007-9 recessions. However, States exposed to the pre-1990 recessions and Covid recession differ in their pre-trends and thus in the extent to which their relative recovery looks complete in levels, though not in trends. For the pre-1990 recessions, the more exposed States are on a relative downward trend due to their higher manufacturing exposure. The recovery, while incomplete in levels, converges to this downward trend. In the Covid recession, the more exposed States are on an upward trend prior to the recession and recover completely both in levels and to their prior relative trend.

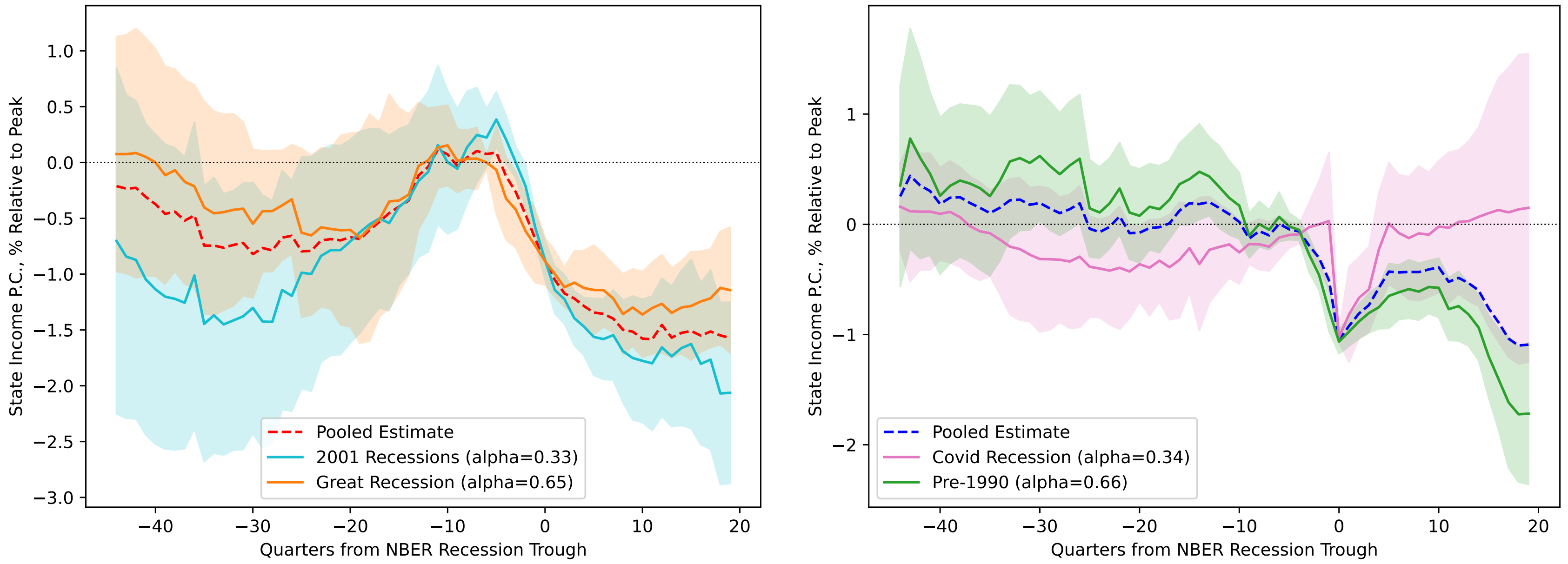
In short, weaker recoveries following a boom-bust cycle are a broad-based phenomenon across sectors and recessions for the 1990-1, 2001, and 2007-9 recessions. In contrast, the strong recoveries from the pre-1990 and Covid recessions are also broad-based, and they do not display any boom-bust dynamics.

Figure 6: Impulse Response Functions of State Income P.C. by Industry and Recession Variation



(a) By Industry: 1990-1, 2001, 2007-9

(b) By Industry: Other Recessions



(c) By Recessions: 1990-1, 2001, 2007-9

(d) By Recessions: Other Recessions

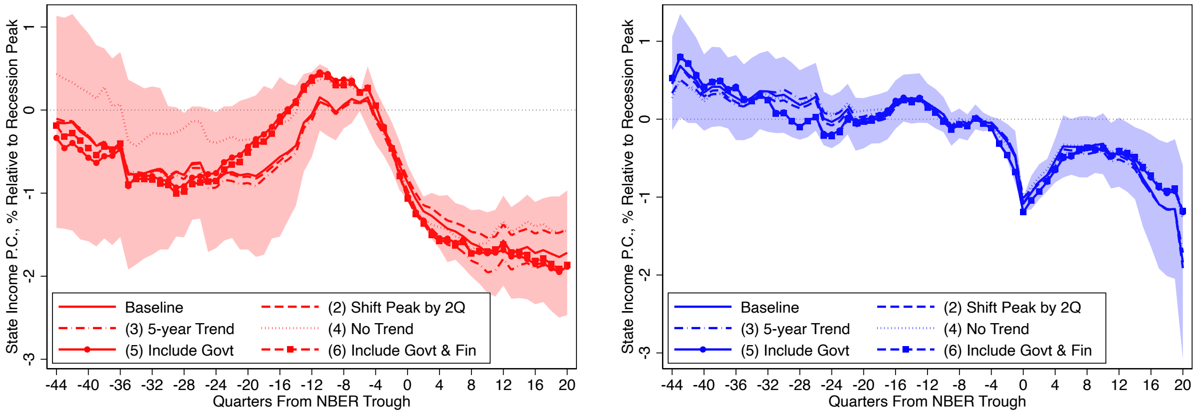
**4.5 Robustness** We conclude our empirical analysis by showing that our main results are robust to a variety of changes in the construction of the instrument, the set of fixed effects, and the sample. We present these robustness checks in Figures 7a to 7f. Each figure contains six panels. The left column shows the IRFs for the 1990-1, 2001, and 2007-9 recessions and the right column for the other recessions. The top panel shows how the IRFs change when we vary the instrument (Figures 7a and 7b), the middle panel varies the fixed effects (Figures 7c and 7d), and the bottom panel changes the sample (Figures 7e and 7f). In each case, we re-estimate the first stage and second stage for each variation.

Figures 7a and 7b show how the IRFs for the 1990-1, 2001, 2007-9 recessions and the other recessions change when we construct the instrument differently. In (2) we construct the peak-to-peak national industry growth rates two quarters prior to the NBER peak and in (3) we construct it using five-year pretrend from the NBER peak. In (4) we omit detrending local recession depth. Neither of these changes materially affects the impulse response functions. In (5) and (6) we include the government and government and finance sectors in local income shares. This means that as well as comparing across private industries we also compare more cyclical private industries with the less cyclical government sector. The main change is that the boom-bust pattern for the 1990-1, 2001, 2007-9 recessions starts earlier and is a bit more pronounced.

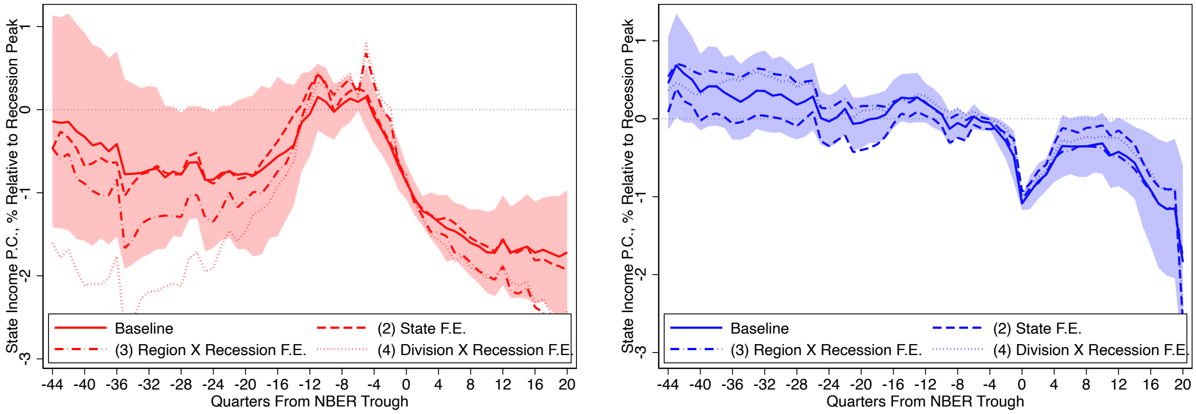
In Figures 7c and 7d we vary the set of fixed effects to proxy for local shocks correlated with national recession exposure. In (2) we include State fixed effects which absorb any permanent difference across States such as permanently different trends correlated with recession exposure. We find that State fixed effects primarily affect the IRF for the fast recoveries by flattening the pretrend and making the recovery look more complete. In (3) and (4) we use Census region and Census division fixed effects interacted with recession fixed effects. These fixed effects capture local shocks that are regional in nature even if they vary across recessions. They primarily change the IRF for the 1990-1, 2001, 2007-9 recessions by increasing the size of both the boom and the bust.

In Figures 7e and 7f we show the sensitivity to the sample. In (2) we drop the three most mining-intensive States and in (3) the three most finance-intensive States, the two categories in which we are least confident that the location of income corresponds to production. The differences from our baseline are minimal. (4) drops the Covid recession, which makes the downward-trend in the other recessions more pronounced. (5) and (6) show only the Great Recession and the 2001 recession, respectively. Both display the boom-bust pattern of our baseline.

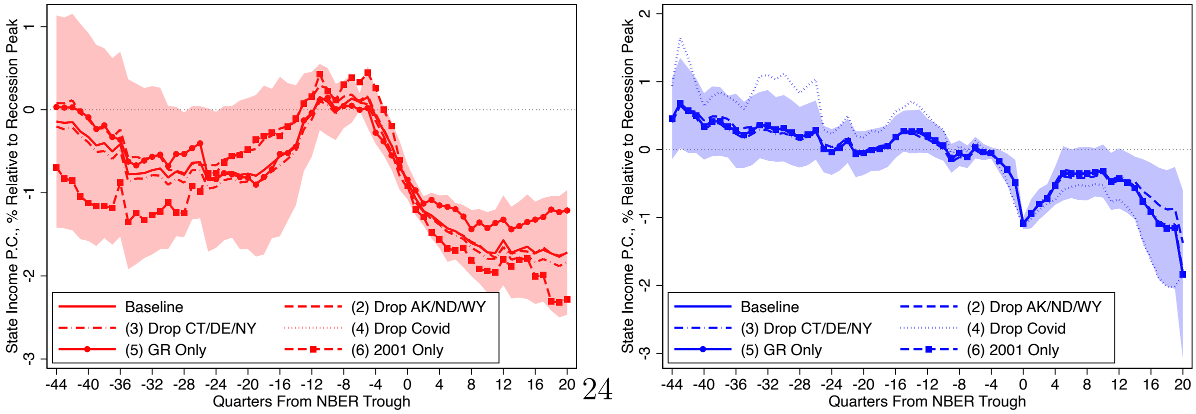
Figure 7: IRFs Robustness


(a) Instrument Variation: 90-1, 01, 07-9

(b) Instrument Variation: Other Recessions


(c) Fixed Effects: 90-1, 01, 07-9

(d) Fixed Effects: Other Recessions


(e) Sample Variation: 90-1, 01, 07-9

(f) Sample Variation: Other Recessions

# 5 Model

The objective of this section is to build a quantitative model that is consistent with the two different types of recessions we document above and then to use that model for policy analysis. The model has two region and two goods, with goods subject to standard New-Keynesian price stickiness. The two-good structure allows for the regions to be differentially exposed to a national recession so we can run the same regressions in the model as we do in the data.

**5.1 Households** Households maximize expected utility subject to their budget constraint. The expected utility function of household $i$ is given by:

$$\mathrm{E}_{i,0} \sum_{t=0}^{\infty} \beta^t \left[ \frac{(C_t)^{1-\sigma}}{1-\sigma} + \psi_t \varepsilon_{\psi t} \frac{D_{i,t}{}^{1-\sigma_d}}{1-\sigma_d} - \varphi_t \frac{L_t{}^{1+\nu}}{1+\nu} \right]$$

where $C_t$ is consumption of a composite nondurable good, $D_{i,t}$ is the durable stock of household $i$ and $L_t$ is total labor supply. $\psi_t$ and $\varphi_t$ are time-varying preference shifters for durable goods consumption and labor supply that keep hours worked and the ratio of nondurable to durable consumption constant along the balanced growth path.[11] $\varepsilon_{\psi t}$ is an exogenous stationary shock to durable preferences that we use to model a boom-bust cycle.

The durable stock $D_{it}$ is specific to the household. We assume that each period only a fraction $(1-\theta^d)$ of households is allowed to re-optimize its durable stock. This formulation, which follows Evans and Ramey (1992) and Orchard, Ramey, and Wieland (2023), reduces the counterfactually high sensitivity of durable consumption to interest rate changes present in standard models, while preserving tractability. Nondurable consumption $C_t$ is identical between households due to consumption insurance and labor supply $L_t$ is identical because it is set by labor unions.

Expectations are specific to household $i$ due to information stickiness as in Auclert, Rognlie, and Straub (2020) and Carroll, Crawley, Slacalek, Tokuoka, and White (2020). The current state at $t$ is common knowledge, so households never violate their budget constraint.

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[11] The process for $\varphi_t$ is such that it implies constant hours along a balanced growth path:

$$\varphi_t = (C_t)^{-\sigma} Z_t$$

where $Z_t$ is the level of productivity of the aggregate economy. The taste for durables, $\psi_t$, contains a productivity component as well as an exogenous stationary process $\varepsilon_{\psi t}$:

$$\psi_t = \bar{\psi} Z_t^{\sigma-\sigma^d}.$$

There is uncertainty about the future path of aggregate shocks and households update their expectations with i.i.d. probability $1-\theta$ in each period.

The aggregate budget constraint and the law of motion for the aggregate durable stock are given by:

$$\begin{aligned}
A_t &= (1+i_{t-1})A_{t-1} + W_t L_t - P_t C_t - \iota P_t D_t - P_t^x X_t \\
D_t &= (1-\delta)D_{t-1} + X_t \\
D_t &= \int_0^1 D_{i,t} di
\end{aligned}$$

where $P_t$ is the price index for nondurable goods, $A_t$ are nominal bond holdings, $i_t$ is the nominal interest rate in terms of nondurable goods, $W_t L_t$ is nominal labor income, $D_t$ is the aggregate durable stock, $P_t^x$ is the price index of durable goods , $X_t$ is the composite durable good and $\iota D_t$ are operating costs from using the durable goods (e.g. gas, insurance), which we assume are denominated in units of nondurable goods.

Durable purchases, $X_t$, include maintenance costs, given by $\chi\delta D_{t-1}$, and new durable purchases, $I_t$. Maintenance costs require households to pay a portion $\chi$ of depreciation as maintenance expenditures in each period. This yields:

$$\begin{aligned}
X_t &= \chi\delta D_{t-1} + I_t \\
I_t &= D_t - (1-(1-\chi)\delta)D_{t-1}
\end{aligned}$$

Households optimally choose the schedule for $\{C_{it}, D_{i,t}, A_{it}, X_{it}\}_{t=0}^{\infty}$ that maximizes their utility given their information set. Labor supply is not chosen directly by the household, but by regional labor unions which we describe later on. The separability of preferences allows us to break up the household problem in two steps. We first solve for the optimal choices of $C_t$ and $A_t$ and, given these, we solve the durable choice problem. The first order conditions for $C_t$ and $A_t$ yield a standard Euler equation:

$$\begin{aligned}
\lambda_t &= \beta \frac{(1+i_t)}{\Pi_{t+1}} \lambda_{t+1} \\
\lambda_t &= (C_t)^{-\sigma}
\end{aligned}$$

where $\lambda_t$ is the Lagrange multiplier on the aggregate budget constraint and $\Pi_t = P_t/P_{t-1}$ is the gross inflation rate for nondurable goods. The optimal choice for $D_{i,t}$ conditional on household $i$ making an adjustment at time $t$ solves:

$$\max_{D_{i,t}} E_t \sum_{s=0}^{\infty} (\beta\theta^d)^s \left[ \psi_{t+s}\varepsilon_{\psi t+s} \frac{((1-(1-\chi)\delta)^s D_{i,t})^{1-\sigma_d}}{1-\sigma_d} - \lambda_{t+s}\iota(1-(1-\chi)\delta)^s D_{i,t} \right]$$
$$- \lambda_t p_t^x D_{i,t} + \sum_{s=0}^{\infty} \beta^s {\theta^d}^{s-1}(1-\theta^d)(1-(1-\chi)\delta)^s \lambda_{t+s} p_{t+s}^x D_{i,t}$$

where ${\theta^d}^s$ is the probability that the durable stock chosen at $t$ survives $s$ periods into the future and $p_t^x = P_t^x/P_t$ is the relative price of the durable good. The first term in brackets, $\psi_t\varepsilon_{\psi t}\frac{((1-(1-\chi)\delta)^s D_{i,t})^{1-\sigma_d}}{1-\sigma_d}$, captures the utility flow of the durable stock in $t+s$. The term $\lambda_{t+s}\iota(1-(1-\chi)\delta)^s D_{i,t}$ measures the cost of operating the durable stock in utils of time $t+s$ while the term $p_t^x D_{i,t}$ measures the cost of purchasing the durable stock in period $t$. The last term captures the resale value of the durable stock if an adjustment opportunity arrives in period $t+s$. All households that re-optimize at $t$ solve the same problem, therefore, we can denote their optimal durable stock choice by $D_t^*$. It can be shown that $D_t^*$ satisfies the following Calvo-type specification[12]:

$$D_t^* = \left(\frac{\Omega_{1,t}}{\Omega_{2,t}}\right)^{\frac{1}{\sigma_d}}$$
$$\Omega_{1,t} = \psi_t\varepsilon_{\psi t+s} + \beta\theta^d(1-(1-\chi)\delta)^{1-\sigma_d}\Omega_{1,t+1}$$
$$\Omega_{2,t} = \lambda_t\left(p_t^x + \iota - \frac{(1-(1-\chi)\delta)}{(1+i_t)\Pi_{t+1}^{-1}} p_t^x\left(cg_{t+1}-1\right)\right) + \beta\theta^d(1-(1-\chi)\delta)\Omega_{2,t+1}$$

where $cg_{t+1} = 1 + \frac{p_{t+1}^x}{p_t^x}$ is the capital gain from selling the stock of durable goods in period $t+1$. The optimal aggregate purchases of durable goods are given by:

$$X_t = (1-\theta^d)\left[D_t^* - (1-(1-\chi)\delta)D_{t-1}\right] + \chi\delta D_{t-1}$$

where the first term captures new durables purchases by households that are allowed to reset their durable stock and the second term captures maintenance expenditures which are incurred by all households, regardless of their re-set status. Aggregate nondurable expenditure, $ND_t$, is defined as the sum of consumption of the nondurable good plus operating costs:

$$ND_t = C_t + \iota D_t$$

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[12] This formulation is analogous to the optimal re-set price in a standard model with Calvo-type price rigidities.

**5.2 Regional Demand** The composite nondurable good is given by:

$$ND_t = \left[\gamma_c ND_{1t}^{\frac{\eta_c - 1}{\eta_c}} + (1-\gamma_c) ND_{2t}^{\frac{\eta_c - 1}{\eta_c}}\right]^{\frac{\eta_c}{\eta_c - 1}}$$

where $ND_{rt}$ denotes consumption of nondurable goods produced in region $r$.

The composite $X_t$ aggregates durable goods produced in each region according to:

$$X_t = \left[\gamma_x X_{1t}^{\frac{\eta_x - 1}{\eta_x}} + (1-\gamma_x) X_{2t}^{\frac{\eta_x - 1}{\eta_x}}\right]^{\frac{\eta_x}{\eta_x - 1}}$$

where $X_{rt}$ denotes purchases of durable goods produced in region $r$.

Similarly, total labor supply is a CES aggregate over labor supplied to each region:

$$L_t = \left[\gamma_\ell L_{1t}^{\frac{\eta_\ell - 1}{\eta_\ell}} + (1-\gamma_\ell) L_{2t}^{\frac{\eta_\ell - 1}{\eta_\ell}}\right]^{\frac{\eta_\ell}{\eta_\ell - 1}}$$

where $L_{rt}$ denotes hours worked in region $r$. $\eta_\ell$ governs the elasticity of substitution of labor supply across regions and $\gamma_\ell$ captures the relative preference of households to work in region 1.

Given these preferences, we have the following regional demand schedules:

$$ND_{1t} = \gamma_c ND_t \left(\frac{P_{1t}}{P_t}\right)^{-\eta_c} \qquad X_{1t} = \gamma_x X_t \left(\frac{P^x_{1t}}{P^x_t}\right)^{-\eta_x}$$

$$ND_{2t} = (1-\gamma_c) ND_t \left(\frac{P_{2t}}{P_t}\right)^{-\eta_c} \qquad X_{2t} = (1-\gamma_x) X_t \left(\frac{P^x_{2t}}{P^x_t}\right)^{-\eta_x}$$

With the corresponding CES price indices given by:

$$P_t = \left[\gamma_c P_{1t}^{1-\eta_c} + (1-\gamma_c) P_{2t}^{1-\eta_c}\right]^{1-\eta_c}$$

$$P^x_t = \left[\gamma_x P^{x\,1-\eta_x}_{1t} + (1-\gamma_x) P^{x\,1-\eta_x}_{2t}\right]^{1-\eta_x}$$

**5.3 Nondurable Goods Production** Nondurable goods are produced by perfectly competitive firms using a technology linear in labor. The problem of a representative firm located in region $r$ is:

$$\max \quad \pi_t = P_{rt} Y_{rt} - W_{rt} L_{rt} \qquad \text{s.t.} \quad Y_{rt} = Z_t Z_r L_{rt}$$

where $Z_t$ is aggregate TFP, $Z_r$ is a region-specific productivity shifter, and $W_{rt}$ is the nominal wage prevailing in region $r$. Under flexible prices, profit-maximizing firms set prices equal to nominal marginal costs:

$$P_{rt} = \frac{W_{rt}}{Z_t}$$

**5.4 Durable Goods** In each region, a continuum of perfectly competitive firms operate with a technology that transforms local nondurable goods into durable goods subject to a congestion externality (McKay and Wieland, 2022). This externality introduces decreasing returns to scale in durable goods production. The technology of a representative firm $i$ in region $r$ is:

$$X_{irt} = Z_r^x M_{irt} \left( \frac{X_{rt}}{\bar{X}_r} \right)^{-\zeta}$$

where $Z_r^x$ is region-specific productivity in durable production, $M_{irt}$ are inputs of locally-sourced nondurable goods, $X_{rt}$ is total durable good production in region $r$ and $\bar{X}_r$ is durable production of $r$ on the balanced growth path. The term $\left( \frac{X_r}{\bar{X}_r} \right)^{-\zeta}$ captures the congestion externality.

The optimal price of the perfectly competitive firm is:

$$P_{rt}^x = \frac{P_{rt}}{Z_r^x} \left( \frac{X_{rt}}{\bar{X}_r} \right)^{\zeta}$$

Firms set prices equal to region-specific marginal costs. $P_r^x$ is the price of non-durable goods produced in region $r$. Parameter $\zeta$, the inverse price-elasticity of durable supply, governs the strength of the congestion externality.

**5.5 Aggregate TFP growth** Total factor productivity $Z_t$ grows at a constant rate $g_{zt} = \bar{g}$.

**5.6 Labor Unions** There is a continuum of labor unions in each region. Each union $j$ supplies a differentiated labor type to a local competitive firm that aggregates all labor types and sells them at price $W_{rt}$ to local nondurable producers. The aggregator is,

$$L_{rt}^d = \left[ \int_0^1 L_{rt}^d(j)^{\frac{\varepsilon^w - 1}{\varepsilon^w}} dj \right]^{\frac{\varepsilon^w}{\varepsilon^w - 1}}$$

where $\varepsilon^w$ measures the elasticity of substitution across labor types within a region and $L_{rt}^d$ is labor demand from nondurable producers located in region $r$.

The labor demand faced by union $j$ is given by:

$$L_{rt}^d(j) = L_{rt}^d \left( \frac{W_{rt}(j)}{W_{rt}} \right)^{-\varepsilon^w}$$

The union chooses wages to maximize the average expected utility across households subject to a Calvo-type friction. The problem of a union $j$ in region $r$ that gets to re-optimize its wage at time $t$ is as follows:

$$\max_{W_{rt}^*(j)} \sum_{s=0}^{\infty} (\beta\theta^w)^s \left[ U_{c_{t+s}} \frac{W_{rt+s|t}^*(j)}{P_{t+s}} L_{rt+s|t}^d(j) - U_{L_{r,t+s}} L_{rt+s|t}^d(j) \right]$$

where:

$$\begin{aligned} L_{rt+s|t}^d(j) &= L_{rt+s}^d W_{rt+s}^{\varepsilon^w} W_{rt}^*(j)^{-\varepsilon^w} \\ U_{L_{rt+s}} &= \varphi_{t+s} L_{t+s}^{\nu} \gamma_\ell^{\frac{1}{\eta_\ell}} L_{rt+s}^{-\frac{1}{\eta_\ell}} \\ U_{c_{t+s}} &= \lambda_{t+s} \end{aligned}$$

where $\theta^{ws}$ is the probability that the wage contract survives $s$ periods into the future, $U_{ct}$ is the marginal utility of consumption and $U_{L_{rt}}$ is the marginal disutility of labor supplied to region $r$. In absence of an adjustment opportunity, the prevailing wage in $t+s$ stays fixed at its period $t$ value. The labor union chooses $W_{rt}^*(j)$ such that it maximizes household utility over the expected duration of the wage contract. Since the problem of all unions adjusting in period $t$ in region $r$ is symmetric, we omit indexing the optimal reset wage by $j$. The optimal wage contract solves:

$$\begin{aligned} w_{rt}^* &= \frac{\varepsilon^w}{\varepsilon^w - 1} \frac{F_{1rt}}{F_{2rt}} \\ F_{1rt} &= \gamma_\ell^{-\frac{1}{\eta_\ell}} \varphi_t L_t^{\nu - \frac{1}{\eta_\ell}} L_{rt}^{\frac{1}{\eta_\ell}} L_{rt}^d w_{rt}^{\varepsilon^w} + \beta\theta^w \Pi_{t+1}^{\varepsilon^w} F_{1r,t+1} \\ F_{2rt} &= \lambda_t L_{rt}^d w_{rt}^{\varepsilon^w} + \beta\theta^w \Pi_{t+1}^{\varepsilon^w - 1} F_{2r,t+1} \end{aligned}$$

where lowercase letters denote real wages and $\Pi_t$ denotes the gross price inflation rate. With perfectly flexible wages, optimality implies that wages equal a constant mark-up over the marginal rate of substitution. Away from this scenario, the wage mark-up will fluctuate across time and unions. This wage dispersion induces a wedge (in terms of *utils*) between hours worked, $L_{rt}$, and effective hours worked, $L^d_{rt}$:

$$L_{rt} = s^w_{rt} L^d_{rt}$$

where $s^w_{rt}$ measures the degree of wage dispersion across unions within a region. This wedge evolves according to:

$$\begin{aligned} s^w_{rt} &= \int_0^1 \left(\frac{W_{rt}(j)}{W_{rt}}\right)^{-\varepsilon^w} dj \\ &= (1-\theta^w)\left(\frac{W^*_{rt}}{W_{rt}}\right)^{-\varepsilon^w} + \theta^w \left(\frac{W_{rt-1}}{W_{rt}}\right)^{-\varepsilon^w} s^w_{rt-1} \\ &= (1-\theta^w)\left(\frac{w^*_{rt}}{w_{rt}}\right)^{-\varepsilon^w} + \theta^w \left(\frac{w_{rt-1}}{w_{rt}}\Pi_t\right)^{-\varepsilon^w} s^w_{rt-1} \end{aligned}$$

The real wage index for jobs located in region $r$ satisfies:

$$w_{rt} = \left[(1-\theta^w){w^*_{rt}}^{1-\varepsilon^w} + \theta^w \left(w_{rt-1}\Pi_t^{-1}\right)^{1-\varepsilon^w}\right]^{\frac{1}{1-\varepsilon^w}}$$

Lastly, the aggregate real wage, $w_t$, is characterized by the following CES index:

$$w_t = \left[\gamma_\ell w_{1t}^{1-\eta_\ell} + (1-\gamma_\ell) w_{2t}^{1-\eta_\ell}\right]^{\frac{1}{1-\eta_\ell}}$$

**5.7 Monetary Policy** The central bank sets the real interest rate according to the following monetary policy rule:

$$1 + r_t = (1 + r_{ss})\left(\frac{L_t}{L}\right)^{\phi_L} \varepsilon_{rt}$$

where $\bar{r}$ is the real rate along the balanced growth path, $L$ is aggregate labor along the balanced growth path and $\varepsilon_{rt}$ is an exogenous shock to the real interest rate.

**5.8 Market Clearing** Regional goods market clearing implies:

$$Y_{rt} = C_{rt} + \frac{P^x_{rt}}{P_{rt}} X_{rt} \qquad \forall \quad r = 1, 2$$

Aggregate output, $Y_t$, is given by:

$$Y_t = \frac{P_{1t}}{P_t} Y_{1t} + \frac{P_{2t}}{P_t} Y_{2t}$$

Lastly, asset market clearing implies:

$$A_t = 0$$

**5.9 Stationary Equilibrium** We normalize all prices by the nondurable price index, $P_t$, and make the economy stationary by expressing all the growing variables relative to aggregate productivity. We denote with lowercase letters these relative variables and solve the model around a zero-inflation balanced growth path with $y_{ss} = l_{ss} = 1$, $w_{ss} = w_{i,ss} = 1$, and equal-sized regions, $p_{1,ss}y_{1,ss} = p_{2,ss}y_{2,ss} = .5y_{ss}$. The stationary equilibrium is defined by a sequence of productivity-adjusted quantities and wages, a sequence of goods prices $\{p_{it}, p^x_{it}\}$, plus a sequence for the real rate $\{r_t\}$ such that, given the realizations for $\{\varepsilon_\psi, \varepsilon_r\}$: (1) household utility and firm profits are maximized, (2) durable and nondurable goods markets clear, and (3) the asset market clears.

**5.10 Calibration** Table 2 shows the calibrated parameters. We calibrate the model to a quarterly frequency. We set the parameters for the household sector as follows. For the degree of household inattention we choose $\theta = .93$, in line with the estimates of Auclert, Rognlie, and Straub (2020). We calibrate the effective discount factor to $\frac{\beta}{1+g_z} = .99$ to match the average real rate during our sample. We calibrate the depreciation rate to match the average depreciation of the stock of private fixed assets plus durable goods in the BEA fixed asset table between 1947-2019. Operating and maintenance costs are computed as in McKay and Wieland (2022). Operating costs include expenditures in households utilities (PCE), expenditures in motor vehicle fuels and fluids (PCE), and taxes on the housing sector. We calibrate $\iota = .005$ to match the average operating costs as a share of the durable goods stock. Maintenance costs are calculated by aggregating household and motor vehicle maintenance expenditures from the Personal Consumption Expenditures (PCE) data, as well as intermediate goods and services from the housing output table. We set $\chi = .17$ to match the average ratio of maintenance costs to depreciation. The taste for durable goods, $\bar{\psi}$, is calibrated to match the average ratio of nondurable consumption to the durable stock during our sample. We set $\theta^d$,the Calvo friction in the durable choice problem, at $\theta^d = .8$. This implies an elasticity of investment to the real rate of -4 (Gilchrist and Himmelberg (1995), Auclert and Rognlie (2018)). We set the elasticity of substitution for durables equal to $\eta_x = 7$ and the elasticity of substitution for nondurables to $\eta_c = 5$. Higher values for these elasticities

Table 2: Calibrated Parameters

| Parameters | | Value |
|---|---|---|
| $1/\sigma$ | Nondurable EIS | .25 |
| $1/\sigma^d$ | Durable EIS | .25 |
| $\bar{\psi}$ | Taste for Durables | 6.3 |
| $\zeta$ | Inverse Price Elasticity of Durable Supply | .1 |
| $\iota$ | Operating cost | 0.005 |
| $\chi$ | Maintenance cost | 0.17 |
| $\delta$ | Depreciation rate | 0.017 |
| $\frac{\beta}{(1+g_z)}$ | Effective Discount factor | 0.99 |
| $\bar{g}$ | Productivity Growth | .005 |
| $Y/Z$ | Output to TFP Ratio | 1 |
| $\nu$ | Inverse Frisch elasticity | 1 |
| $\phi_L$ | Taylor Rule Coefficient - Output | 0 |
| $\eta_c$ | Elasticity of Substitution - Nondurables | 5 |
| $\eta_x$ | Elasticity of Substitution - Durables | 7 |
| $\eta_\ell$ | Elasticity of Substitution - Labor Supply | 5 |
| $\varepsilon_w$ | Elasticity of Substitution - Labor Demand | 7 |
| $\theta$ | Degree of Information Stickiness | .93 |
| $\theta^d$ | Calvo Parameter - Durable Consumption | .8 |
| $\theta^w$ | Degree of Wage Stickiness | .9 |
| $\gamma_x$ | Regional Bias in Durable Demand | .5 |
| $\gamma_\ell$ | Regional Bias in Labor Supply | .5 |
| $\gamma_c$ | Regional Bias in Nondurable Demand | .5 |
| $Z_1^x$ | Productivity of Investment Sector in Region 1 | 1.04 |
| $Z_2^x$ | Productivity of Investment Sector in Region 2 | .95 |
| $Z_1$ | Productivity of Nondurable Sector in Region 1 | .98 |
| $Z_2$ | Productivity of Nondurable Sector in Region 2 | 1.01 |

imply stronger expenditure switching effects in response to changes in prices across regions. We choose these values to reflect the relatively lower tradability of nondurable goods which we characterize as mostly being labor services. Lastly, we set the elasticity of substitution of labor supply between regions at $\eta_\ell = 5$.

We calibrate the production side as follows. We normalize the output-to-TFP ratio to one in the stationary equilibrium. The deterministic component of TFP growth, $g_Z$, is calibrated to match the average quarterly growth rate of real GDP per capita over the period 1947-2019. We calibrate the inverse supply elasticity of durable goods to $\zeta = .1$ based on House and Shapiro (2008). We set the elasticity of substitution of labor demand across unions to $\varepsilon_w = 7$. This is in the middle range of values used in the literature and implies a wage markup of 15% in the steady state. We set the degree of wage stickiness to $\theta_w = .9$, which implies that unions re-optimize wages on average every 10 quarters.

We set the productivity parameters in the durables sector, $Z_1^x$ and $Z_2^x$, and nondurables sector, $Z_1$ and $Z_2$, to generate heterogeneity in the industrial composition between regions.

Specifically, we choose $Z_1^x$ such that the participation of region 1 in total durable production is 55%. Then $Z_2^x$ is set to guarantee that the relative aggregate price of durable goods is equal to one in steady state (that is, $p_{ss}^x = 1$). Lastly, we choose productivity values in the nondurable sector to ensure that both regions have the same level of steady-state output. As a result, Region 1 is relatively specialized in the production of durable goods, while Region 2 is relatively specialized in nondurable goods.

**5.11 Matching the Data** We model boom-bust recessions as the result of a fake news shock to households' taste for durables $\psi_t$. We assume a two-wave information structure to construct the fake news shock which we briefly describe next. Appendix C provides further details. In period $t = 0$, news arrive about an increase in $\psi_t$ beginning in period $s > 0$. This constitutes the first wave of information. Starting at $t = 0$, agents gradually learn of this future path at a rate $1 - \theta$, where $\theta \in [0, 1)$ captures the degree of information stickiness. Households who update their information set expect a higher return on durable consumption beginning in period $s$. In anticipation of this, they build up their durable stock, which boosts output and the investment share. Because households update their information set infrequently, this results in a gradual build-up of the aggregate durable stock. In period $z < s$, a second wave of information begins. In each period $t \geq z$, a share $1 - \theta$ of agents who expect $\psi_t$ to increase at time $s$ learn that the taste for durables will not change. Households who receive this new piece of information find themselves with an excess stock of durable goods they wish to liquidate. Initially, this results in a deceleration of the process of accumulation of durable goods at the aggregate level. Accumulation decelerates but does not come to an immediate halt. This is because the stock of households that still expect $\psi_t$ to increase is large relative to those who learn of the second wave. As the second wave of information disseminates, the liquidation of excess stocks generates a bust in output, a sustained decrease in the investment share, and a slow recovery of the economy relative to the elevated pretrend.

We generate a V-shaped recession pattern for the pre-1990 and Covid recessions using a temporary monetary policy shock. In practice, any transitory shock in the model will generate a V-shaped recession in the model. We choose monetary policy shocks because they are considered important drivers of pre-1990 recessions (Coibion, 2012; Romer and Romer, 2023). One can interpret the Covid recession as a period in which the price of consumption today relative to the future—the real interest rate—was high due to health risk associated with certain types of consumption. An unexpected increase in the real interest rate induces intertemporal substitution away from consumption and investment that cause output to temporarily drop below trend before bouncing back once the monetary shock recedes. Due to the importance of intertemporal motives in such shocks, we call them intertemporal shocks.

We model the relatively weaker trend of the more exposed region as the result of a change in $\gamma_x$, the regional bias in durable demand. A change in $\gamma_x$ triggers the reallocation of durable household purchases across regions, holding total purchases fixed. This allows us to compute the path of $\gamma_x$ that rationalizes a given time path for the differential in growth rates between regions, absent any national recessions. Given the linearity of the model, we can then additively feed in the aggregate shocks that generate national recessions, as discussed above.

We solve the model in the sequence space using the methods developed by Auclert, Bardóczy, Rognlie, and Straub (2021). We then simulate the path of the economy for different shocks that generate heterogeneous recessions and recovery dynamics. Importantly, we keep all the parameters that affect the steady state fixed across recessions, which means that all differential dynamics can be traced back to the type of shock that hits the economy. Next, using the simulated data, we compute the model analog of the relative recession impulse response function in Figure 4. Specifically, we estimate the same regression (3) using a Bartik instrument in the model as we do in the data.

We estimate the path of $\gamma_x$[13] and the parameters that govern the shock processes to match the impulse responses in Figure 4. We assume AR(1) processes for both the monetary policy and taste for durables shocks:

$$\begin{aligned} \varepsilon_t^r &= \rho_r e_{t-1}^r + e_t^r, \qquad e_t^r \overset{\text{iid}}{\sim} N(0, \sigma_r^2) \\ \varepsilon_t^\psi &= \rho_\psi \varepsilon_{t-1}^\psi + e_t^\psi, \qquad e_t^\psi \overset{\text{iid}}{\sim} N(0, \sigma_\psi^2) \end{aligned}$$

where $\rho_x$ and $\sigma_x$ are the persistence and standard deviation of shock $x$. For each alternative explanation, we estimate the persistence of the shock processes. We also estimate the timing of each information wave, $s$ and $z$. Let $f(\mathbf{\Gamma})$ denote the vector of model-implied cross-sectional impulse responses evaluated at parameter values $\mathbf{\Gamma}$. Let $\boldsymbol{\beta}$ denote the vector of empirical impulse responses estimated in Section 4 .

We estimate the parameters by solving:

$$\hat{\mathbf{\Gamma}} = argmin_{\mathbf{\Gamma}} \quad (\boldsymbol{\beta} - f(\mathbf{\Gamma}))^{'} \mathcal{W}^{-1} (\boldsymbol{\beta} - f(\mathbf{\Gamma}))$$

where $\mathcal{W}$ is a diagonal weighting matrix containing the estimated variances of the elements of $\beta$ and $\hat{\mathbf{\Gamma}}$ is the value of the parameter vector that minimizes the weighted distance between the model-implied and empirical impulse responses. Table 3 presents the estimated parameters.

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[13] In particular, we estimate a single path of $\gamma_x$, which means that both types of recessions occur around the same relatively weaker pretrends.

Table 3: Estimated Patameters

| | | Value |
|---|---|---|
| **Intertemporal *vs.* Boom-bust** | | |
| Persistence of Monetary Policy Shock | $\rho_r$ | .946 |
| Persistence of Taste Shock | $\rho_\psi$ | 1 |
| Fake News Date | s | 17 |
| Second Wave of News Date | z | 14 |

Throughout the exercise, we calibrate the standard deviation of each aggregate shock to match the average depth of the recession in our sample, which is 5.3%.

In Figure 8 we show that when recessions are driven by different aggregate shocks, the model can generate impulse response functions that closely match the cross-sectional estimates for the 1990-1, 2001, and 2007-9 recessions. Regions that are more exposed to the boom-bust recession have a relatively higher above-trend growth rate due to the prior boom. Recoveries in these regions will look weaker because they can never catch up to this inflated pre-recession trend. The estimation favors a slight downward trend in the more exposed regions due to the negative pretrend prior to the boom.

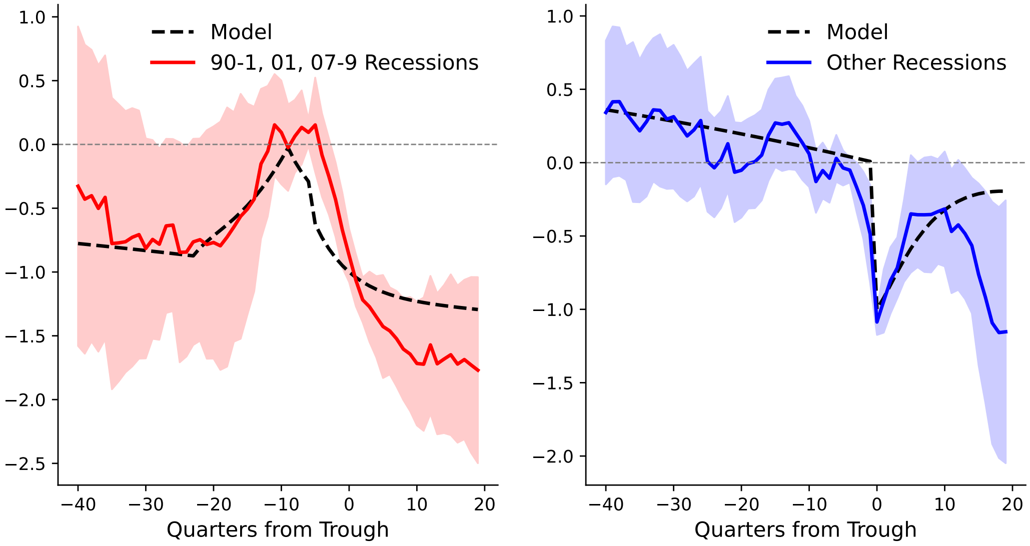
Intertemporal shocks, such as a monetary policy shock, do not affect the pretrend and represent only a temporary departure from it. Thus, these shocks predict a V-shaped relative recovery in the absence of pretrends. However, our estimates point to a significantly lower trend growth rate in the more exposed States which helps the model match the observed recovery in the data.

**5.12 Policy Analysis** We next show that distinguishing between boom-bust cycles and intertemporal shocks is important for policy in the recovery. Specifically, for each recession we solve for the path of the real interest rate $R^*$ that closes the aggregate output gap starting at the recession trough. We scale each recession to a 5.2% peak-to-trough decline in aggregate output, which is the empirical average for both types of recessions. Figure 9 shows the 10-year $R^*$ zero coupon rate computed using the expectations hypothesis.

The model implies that long-run $R^*$ persistently declines following a boom-bust cycle, reaching a trough of 20 basis points. In contrast, the V-shaped monetary policy recession predicts an increase of long-run $R^*$ of several basis points.

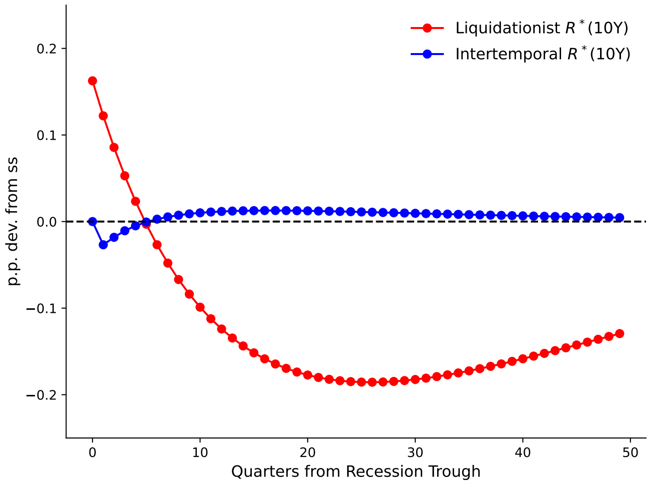
These distinct patterns for $R^*$ are due to the dynamics of the capital stock. Following a boom-bust cycle, the economy finds itself with excess capital. Investment is persistently low and aggregate demand needs to be supported using a low real interest rate. However, an

Figure 8: Matching the Recession IRF - Liquidationist *vs.* Intertemporal



intertemporal shock that delayed investment and consumption implies that the capital stock is below steady-state in the recovery. Thus, there is pent-up demand for investment which pushes up $R^*$ in the recovery path. This implies that the degree of monetary accommodation required in the recovery depends importantly on the type of shock.

Figure 9: $R_t^*$ - Liquidationist *vs.* Intertemporal



# 6 Conclusion

The recoveries from the 1990-1, 2001, and 2007-9 recessions have been weak relative to other postwar business cycles. We provide new cross-State evidence that suggests the recovery patterns are due to different shocks: Boom-bust cycles in the 1990-1, 2001, and 2007-9 recessions give rise to weak recoveries and intertemporal shocks in the pre-1990 and 2020 recessions predict strong recoveries. Our model that quantitatively matches these patterns shows that recessions caused by boom-bust cycles require extended periods of accommodative policy relative to recessions caused by intertemporal shocks.

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# A Figures

Figure 10: Impulse Response Function of State Personal Income by Recession Group Double-Clustering by State and Recession

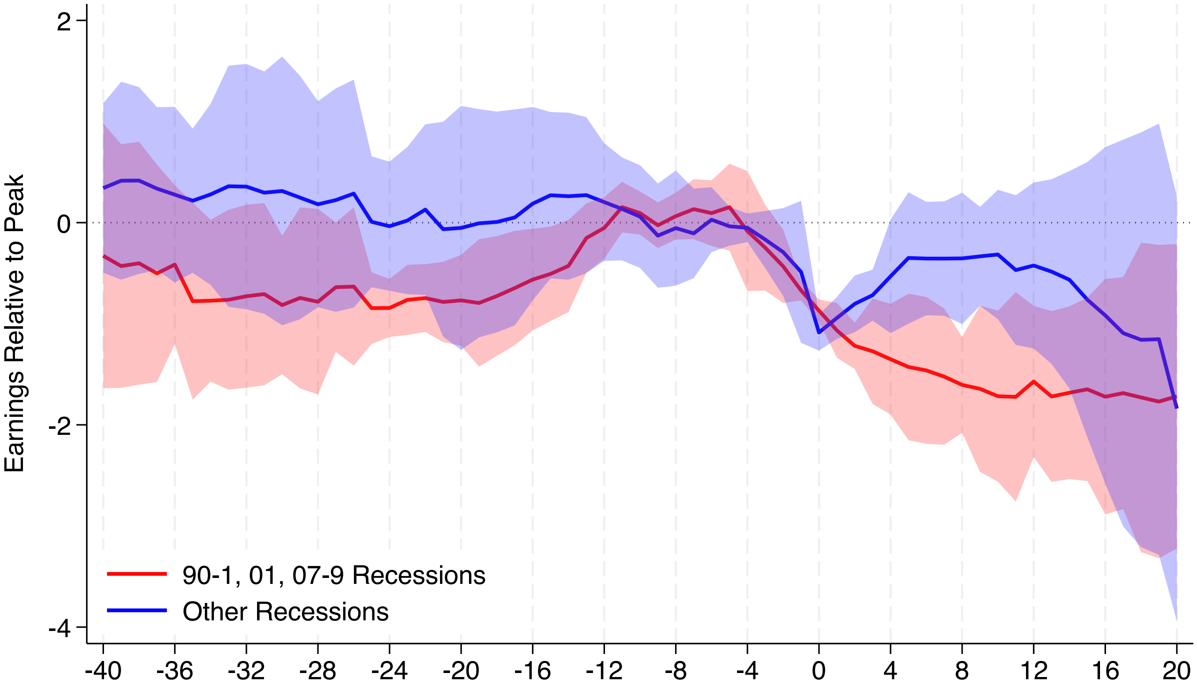
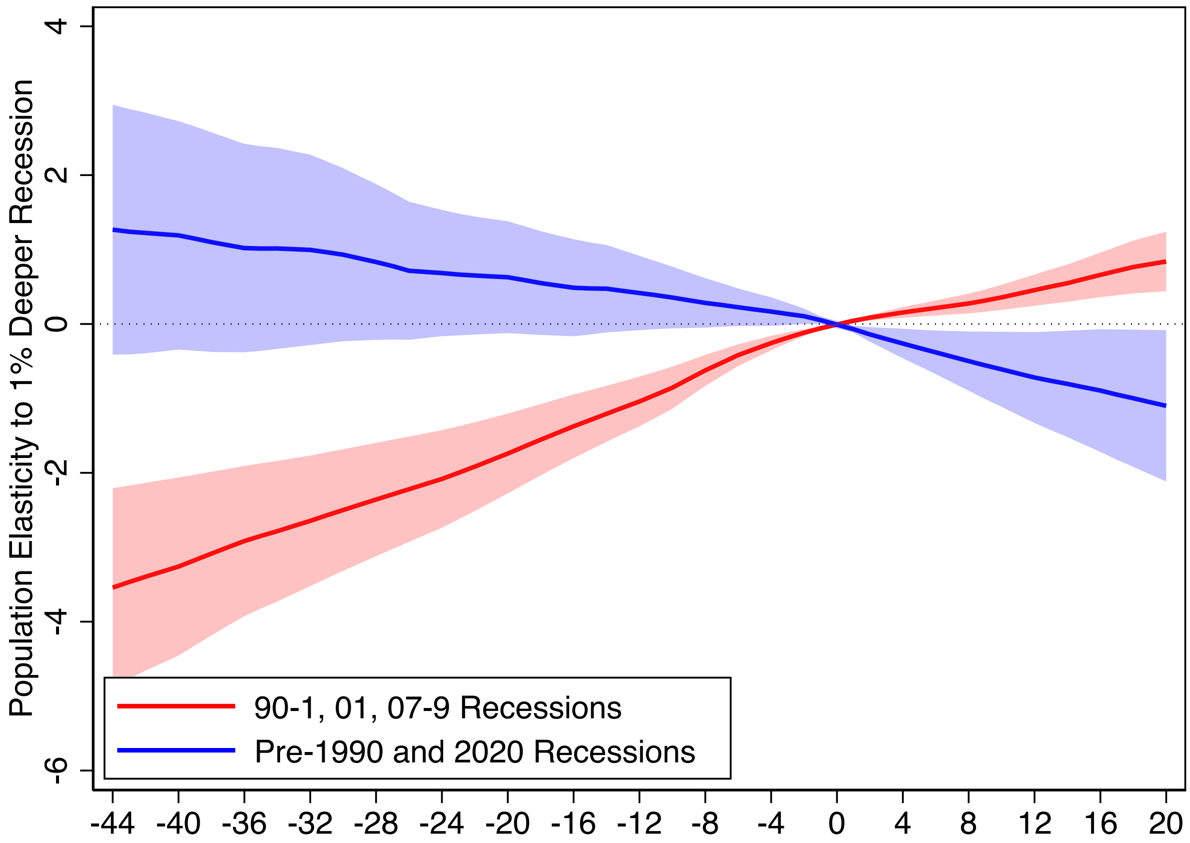
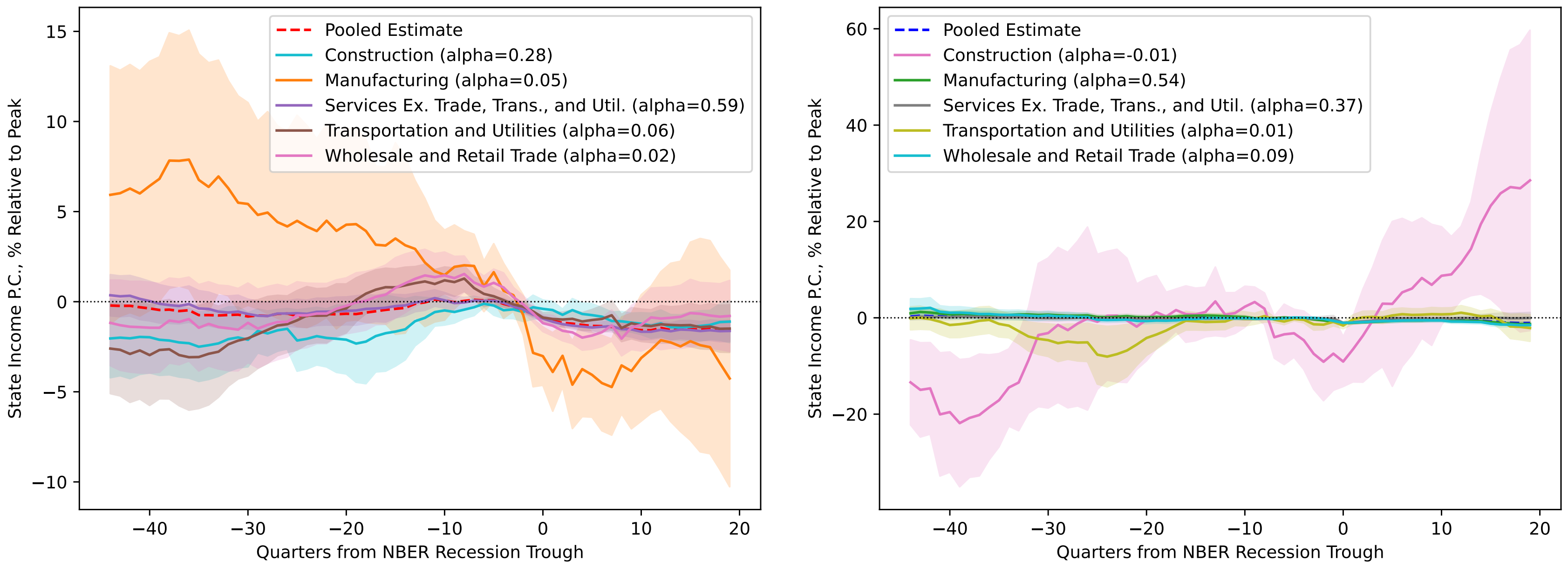


Figure 11: Recession Impulse Response Function for Population



## B Rotemberg Weights

Figure 12: Impulse Response Functions based on Major Industry and Recession Variation



(a) Industry: 1990-1, 2001, 2007-9

(b) Industry: Other Recessions

(c) Recessions: 1990-1, 2001, 2007-9

(d) Recessions: Other Recessions

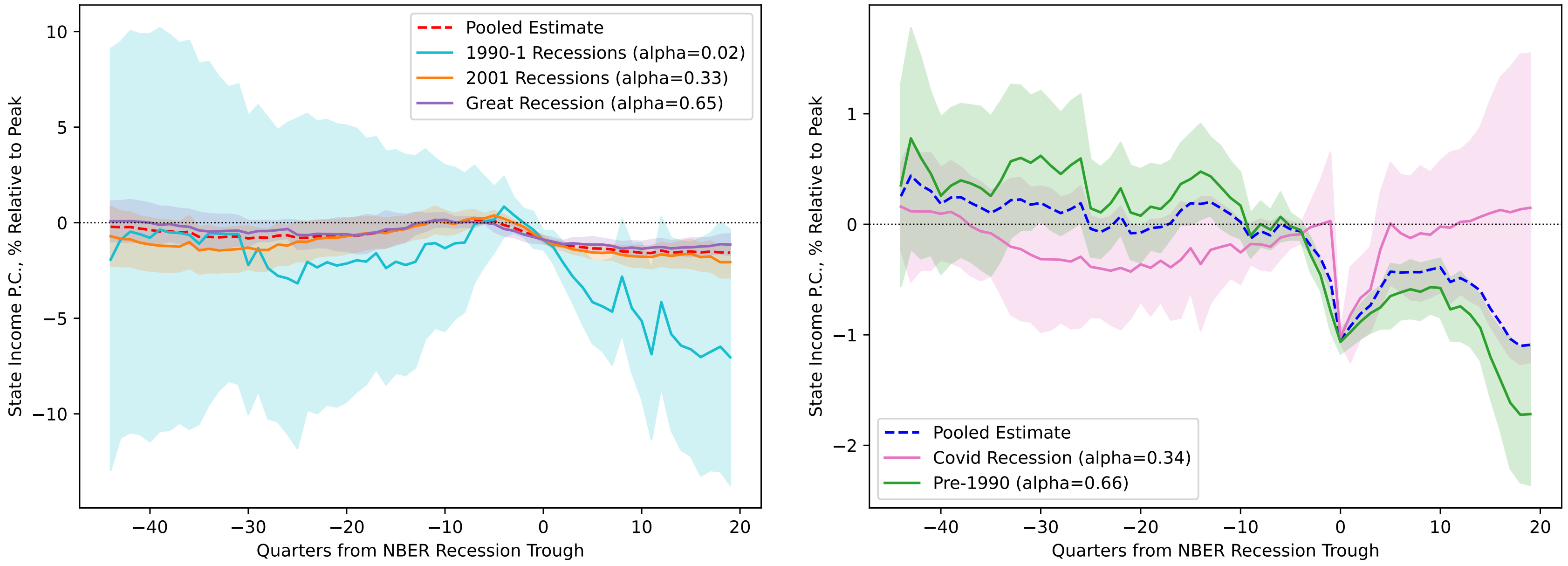
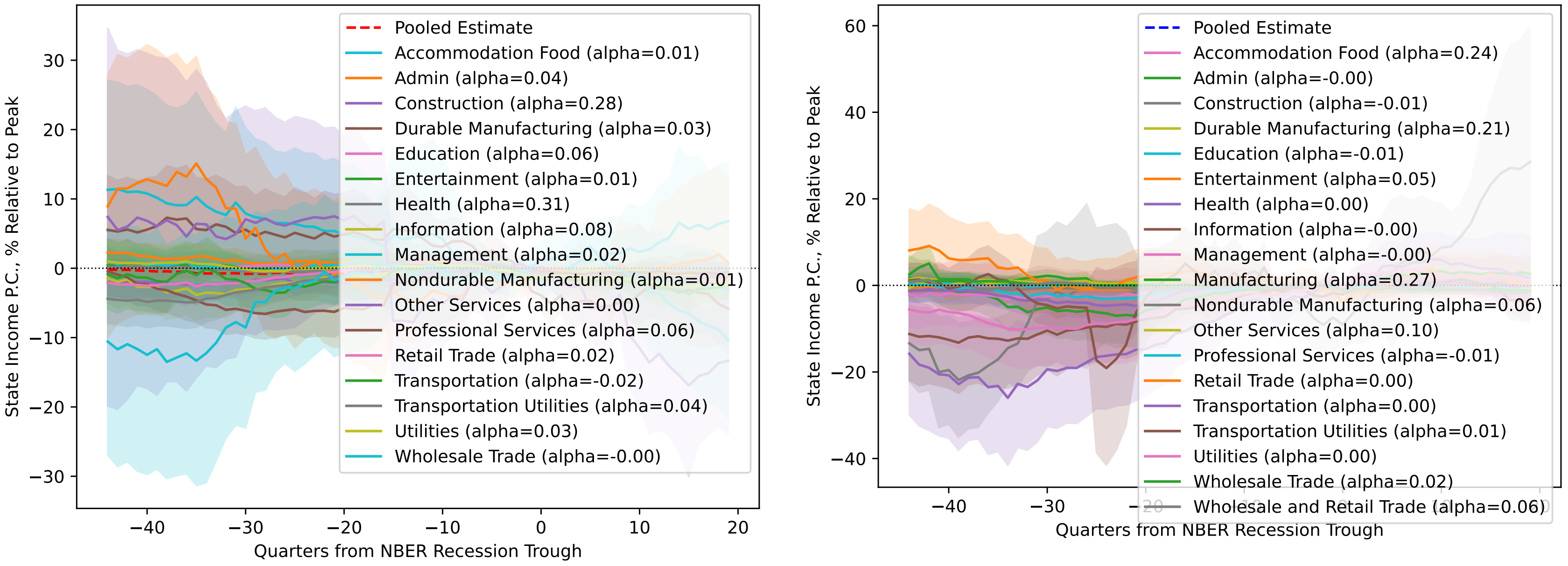
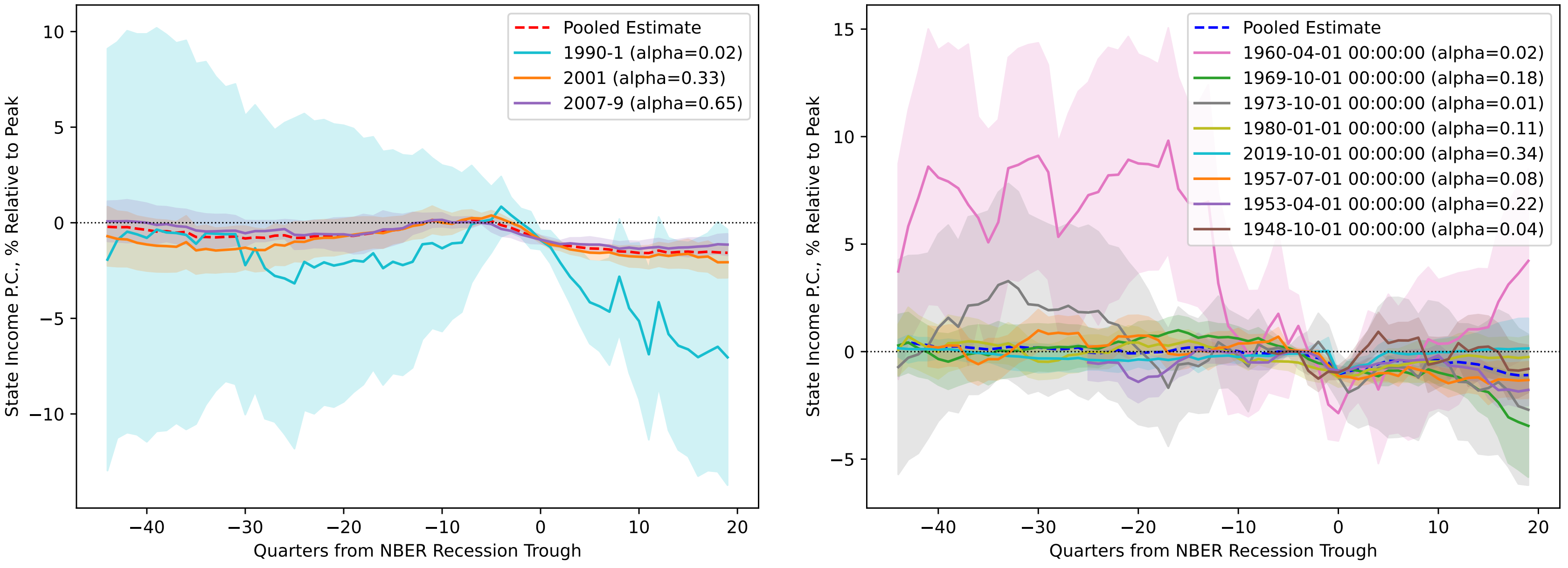


Figure 13: Impulse Response Functions based on Industry and Recession Variation


(a) Industry: 1990-1, 2001, 2007-9

(b) Industry: Other Recessions


(c) Recessions: 1990-1, 2001, 2007-9

(d) Recessions: Other Recessions

# C Information Structure

This appendix details how we model boom-bust or liquidationist recessions using a fake news shock to households's taste for durables $\psi_t$.

**Notation** Let $J^{i,o}$ be the full-information Jacobian for an input $i$ and output $o$. Each column $s$ of this matrix tracks the response of output $o$ to a one-time innovation to input $i$ in period $s$. Concretely, we have

$$J^{o,i} = \begin{pmatrix} \frac{\partial o_0}{\partial i_0} & \cdots & \frac{\partial o_{T-1}}{\partial i_0} \\ & \ddots & \\ \frac{\partial o_{T-1}}{\partial i_0} & \cdots & \frac{\partial o_{T-1}}{\partial i_{T-1}} \end{pmatrix} \qquad J^{o,i}_{t,s} = \frac{\partial o_t}{\partial i_s}$$

Throughout, we fix $i = \psi$ and $o = y_t$ so we omit superscripts. We use the notation $J_{[a\bullet b,c\bullet d]}$ to denote the submatrix of $J$ from row $a$ to $b$ and column $c$ to $d$, and is zero otherwise. We label the first column and row as 0, so the final column and row are labeled $T-1$. We also define $0_m$ as a row of $m$ zeros and $0_{m,n}$ as an $m \times n$ matrix of zeros. The taste shock is a $T \times 1$ vector $\psi_{0,T-1} = (\psi_t)_{t=0}^{T-1}$. We denote the subsequence from $t$ to $t+k$ by $\psi_{t,t+k}$. Under full information the output sequence, $y_{0,T-1}$, in response to the shock path $\psi_{0,T-1}$ is:

$$y_{0,T-1} = J\psi_{0,T-1}$$

Importantly, we can construct impulse responses that incorporate different information structures by combining different columns of the full information Jacobian $J$. Below we detail our approach.

**Fake News Shocks** We assume the following two-wave information structure to model the fake news shock. In period $t = 0$, news arrive about an increase in $\psi_t$ starting at time $s > 0$. This is the first wave of information. We denote the shock sequence associated to this wave by $\psi^0_{0,T-1}$:

$$\psi^0_{0,T-1} = \begin{pmatrix} 0_{0,s-1} \\ \bar{\psi}_{s,T-1} \end{pmatrix}$$

where $\bar{\psi}_k > 0$ for some $k \geq s$. Starting at $t = 0$, agents learn of the sequence $\psi^0_{0,T-1}$ at rate $1-\theta$, where $\theta$ governs the degree of information stickiness. Households that update their information set expect a higher return from durable consumption beginning in period $s$. In anticipation of this, they build-up their durable stock which boosts output and the investment share. Because households update their information set infrequently this results in a gradual build-up of the aggregate durable stock. At time $z < s$ a new wave of information starts. In each period $t \geq z$, a share $1-\theta$ of the agents that expect the shock sequence to be $\bar{\psi}_{t,T-1}$ learn that the sequence will instead be $\psi_{t,T-1} = \mathbf{0}$. This is equivalent to learning of a shock with path given by $\tilde{\psi}_{t,T-1} = -\psi^0_{t,T-1}$. Households that receive this new piece of information, find themselves with an excess stock of durable goods that they wish to liquidate. Initially, this results in a deceleration of the accumulation process of durable goods at the aggregate level. Accumulation decelerates but does not come to an immediate halt. This is because the stock of households that still expect the shock sequence $\psi^0_{0,T-1}$ is large relative to the stock that learns of $\tilde{\psi}_{0,T-1}$. As the second wave of information disseminates, the liquidation of excess stocks generates a bust in output, a sustained decrease in the investment share and a slow recovery of the economy relative to the preceding boom period. Next, we provide further details on how we implement and put together each of these information waves.

**Implementation of the first wave** We can construct the outcome of the first information wave as the following series of learning steps:

$$
\begin{aligned}
y_{0,T-1} &= (1-\theta) J \psi^0_{0,T-1} && \text{[learn at 0]} \\
&+ \theta(1-\theta) \begin{pmatrix} 0_{1,1} & 0_{1,T-1} \\ 0_{T-1,1} & J_{[0\bullet T-2, 0\bullet T-2]} \end{pmatrix} \psi^0_{0,T-1} && \text{[learn at 1]} \\
&+ \theta^2(1-\theta) \begin{pmatrix} 0_{2,2} & 0_{2,T-2} \\ 0_{T-2,2} & J_{[0\bullet T-2, 0\bullet T-2]} \end{pmatrix} \psi^0_{0,T-1} && \text{[learn at 2]} \\
&\vdots \\
&+ \theta^{T-1}(1-\theta) \begin{pmatrix} 0_{T-1,T-1} & 0_{T-1,1} \\ 0_{1,T-1} & J_{[0\bullet 0, 0\bullet 0]} \end{pmatrix} \psi^0_{0,T-1} && \text{[learn at } T-1\text{]}
\end{aligned}
$$

The summation representation is given by:

$$
y_{0,T-1} = \left[ \sum_{k=0}^{T-1} \theta^k (1-\theta) \begin{pmatrix} 0_{k,k} & 0_{k,T-k} \\ 0_{T-k,k} & J_{[0\bullet T-1-k, 0\bullet T-1-k]} \end{pmatrix} \right] \psi^0_{0,T-1}
$$

where each term $k$ in the summation captures the response of households that learn about the shock sequence $\psi^0_{0,T-1}$ in period $t = k$. We can define the sticky-information Jacobian $S$ such that the outcome effect of the first wave is then

$$
y_{0,T-1} = S \psi^0_{0,T-1}
$$

$S$ can be constructed recursively using

$$S_{[k\bullet T-1,k\bullet T-1]} = S_{[k\bullet T-1,k\bullet T-1]} + \theta^k(1-\theta)J_{[0\bullet T-1-k,0\bullet T-1-k]}, \qquad k = 0,...,T-1$$

**Implementation of the second wave** The second wave of information, which starts at $z < s$, gradually updates the information set of households that expect the shock sequence $\psi^0_{0,T-1}$ by feeding in the sequence $\tilde{\psi}_{0,T-1} = -\psi^0_{0,T-1}$. We refer to the stock of households that believe the shock sequence to be $\psi^0_{0,T-1}$ as believers. In each period $t \geq z$, a portion of believers learns that the sequence will be $\psi_{0,T-1} = 0$ and the remaining believers only learn of the current realization $\tilde{\psi}_t$. This means the latter know that the taste for durables did not change at $t$, $\psi_t = 0$, but still expect $\psi^0_{t+k}$ for $k > 0$.

For implementation, we need to keep track of the stock of households that expect $\psi^0_{0,T-1}$ at each point of time. Every period the flow of new believers is given by:

$$\text{new believers}_t = (1-\theta)\theta^t, \qquad t = 0,...,T-1$$

These are the households that continue to learn about the first wave of information. Next, we assume that believe updating from the second wave of information happens immediately after the first wave and, as mentioned before, it can only affect the current stock of believers. Current believers are the sum of past believers and new believers. Starting from $t \geq z$, each period a fraction $(1-\theta)$ of them gets converted to non-believers (i.e. learns about the second wave):

$$\text{new non-believers}_t = \begin{cases} 0, & \text{if} \quad t < s \\ (1-\theta)(\text{believers}_{t-1} + \text{new believers}_t), & \text{if} \quad t \geq z \end{cases}$$

This means that the stock of believers is simply past believers plus the net change in believers:

$$\text{believers}_t = \text{believers}_{t-1} + \text{new believers}_t - \text{new non-believers}_t$$

We can compute the sticky information Jacobian associated to the second wave as follows:

$$
\begin{aligned}
\tilde{y}_{0,T-1} = {} & \text{new non-believers}_z \begin{pmatrix} 0_{z,z} & 0_{z,T-z} \\ 0_{T-z,z} & J_{[0\bullet T-z-1,0\bullet T-z-1]} \end{pmatrix} \tilde{\psi}_{0,T-1} && \text{[unlearn at } z\text{]} \\
& + \text{believers}_z \begin{pmatrix} 0_{z,1} \\ J_{[0\bullet T-1-z,0]} \end{pmatrix} \tilde{\psi}_z \\
& + \text{new non-believers}_{z+1} \begin{pmatrix} 0_{z+1,z+1} & 0_{z+1,T-z-1} \\ 0_{T-z-1,z+1} & J_{[0\bullet T-z-2,0\bullet T-z-2]} \end{pmatrix} \tilde{\psi}_{0,T-1} && \text{[unlearn at } z+1\text{]} \\
& + \text{believers}_{z+1} \begin{pmatrix} 0_{z+1,1} \\ J_{[0\bullet T-2-z,0]} \end{pmatrix} \tilde{\psi}_{z+1} \\
& \vdots \\
& + \text{new non-believers}_{T-1} \begin{pmatrix} 0_{T-1,T-1} & 0_{T-1,1} \\ 0_{1,T-1} & J_{[0\bullet 0,0\bullet 0]} \end{pmatrix} \tilde{\psi}_{0,T-1} \Bigg\} \\
& + \text{believers}_{T-1} \begin{pmatrix} 0_{T-1,1} \\ J_{[0\bullet 0,0]} \end{pmatrix} \tilde{\psi}_{T-1} && \text{[ unlearn at } T-1\text{]}
\end{aligned}
$$

We can define the sticky-information Jacobian W such that the outcome effect of the second wave is:

$$
\tilde{y}_{0,T-1} = W\tilde{\psi}_{0,T-1}
$$

$W$ can be constructed recursively using:

$$
\begin{aligned}
W^1_{[k\bullet T-1,k\bullet T-1]} &= W^1_{[k\bullet T-1,k\bullet T-1]} + \text{new non-believers}_k J_{[0\bullet T-1-k,0\bullet T-1-k]}, \qquad && k = s, ..., T-1 \\
W^2_{[k\bullet T-1,k]} &= \text{believers}_k J_{[0\bullet T-1-k]}, \qquad k = s, ..., T-1 \\
W &= W^1 + W^2
\end{aligned}
$$

**Combining both waves** The total effect of the two waves is

$$
\begin{aligned}
y_{0,T-1} &= S\psi^0_{0,T-1} + W\tilde{\psi}_{0,T-1} \\
&= (S - W)\psi^0_{0,T-1}
\end{aligned}
$$

The matrix $K = S - W$ governs the transmission of a fake news shock with path given by $\psi^0_{0,T-1}$.