Online Appendix for:
Age Structure and the Impact of Monetary Policy[*]

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- *JEL Codes*: E32, E52, J11

Online Appendix

This appendix contains supplementary material for the paper "Age Structure and the Impact of Monetary Policy." Specifically,

- Section 1 describes the construction of the **monetary policy shocks**.

- Section 2 contains various **robustness checks** for our baseline specification in equation (1) of the paper. We consider wide age bins estimated together, aggregation of states to BEA regions, elimination of small states, and subsample stability.

- In section 3, we control for various **state characteristics** that might be correlated with age structure. We control for state fixed effects, employment in cyclically sensitive sectors, state personal income, housing related characteristics, and other demographic characteristics. In each case, we include the level of the variable, as well as the variable interacted with the monetary policy shocks.

- In section 4, we control for the **fraction of young and small firms** in a state. In each case, we include the level of the variable, as well as the variable interacted with the monetary policy shocks.

- Section 5 describes the **data** used in the paper.

1 Monetary Policy Shocks

This appendix explains the construction of our monetary policy shock series. This identification method involves using intra-day data on federal funds futures contracts around the time of monetary policy announcements. Monetary policy shocks are estimated as the change in the federal funds rate implied by the current month federal funds futures contract in a relatively short window of time around the FOMC announcement. By considering a sufficiently narrow window around the FOMC announcement, one can be reasonably certain that no other news caused the change in the futures rates.

We construct our shock series in two steps. First, we obtain raw shocks from the policy announcements. Second, we aggregate these shocks to a quarterly frequency.

The raw shocks to monetary policy $\left(\epsilon_\tau^{m,hf} \right)$ are defined as follows:

$$\epsilon_\tau^{m,hf} = \frac{\overline{d}_\tau}{\overline{d}_\tau - d\left(\tau \right)} \times \left(i_{\tau + \Delta_1} - i_{\tau - \Delta_0} \right),$$

Here τ is the date and time of a FOMC announcement, $i_{\tau + \Delta_1}$ is the federal funds rate implied by the current month federal funds futures contract Δ_1 minutes after the FOMC announcement, while $i_{\tau - \Delta_0}$ is the rate implied by futures markets Δ_0 minutes before the announcement. We consider a one hour window around the announcements, from fifteen minutes prior to the announcement to forty-five minutes after the announcement. Positive values of $\epsilon_\tau^{m,hf}$ here imply unexpected increases (monetary contractions) in the federal funds rate and vice-versa. The coefficient multiplying the change in the interest rate, accounts for the fact that the settlement price of federal funds futures contracts is based on the realized average effective federal funds rate for the calendar month of the contract and the monetary policy shock implicit in the announcement only affects the federal funds rate over the remainder of the month. Here $\overline{d}$ is the maximum number of days in the month and $d\left(\tau \right)$ is the day of the month of the FOMC announcement.

Following Ottonello and Winberry (2018), we aggregate the high-frequency shocks to a quarterly frequency using a weighted moving average of the raw shocks,

$$\epsilon_t^m = \sum_{\tau \in t} \frac{\overline{d}_t - d\left(t, \tau \right)}{\overline{d}_t} \times \epsilon_\tau^{m,hf} + \sum_{\tau \in t-1} \frac{d\left(t-1, \tau \right)}{\overline{d}_t} \times \epsilon_\tau^{m,hf}.$$

Here t measures time in quarters and the ϵ_t^m are the quarterly aggregated monetary policy shocks that we use in our analysis. $\overline{d}_t$ is the number days in quarter t, and $d(t, \tau)$ is the day in quarter t of announcement τ. This method of aggregating shocks implies that an announcement made on the last day of a quarter will have a very small weight on the current quarter, but a relatively large impact on the next quarter. It is based on the idea that shock at the very end of quarter $t-1$ looks much more like a shock at the very beginning of quarter t than a shock at the very beginning of quarter $t-1$.

Trading in federal funds futures markets began in October 1988. Following Gürkaynak, Sack, and Swanson (2005), we begin our sample in 1990 and end in 2008 when interest rates hit the zero lower bound. We use the federal funds futures shocks from Gürkaynak, et al. (2005) and Gorodnichenko and Weber (2015). Over our baseline sample period of 1990-2008, there were eight scheduled Federal Open Markets Committee (FOMC) meetings in every calendar year. As discussed in detail in Gürkaynak, et al. (2005), the current practice of issuing a press release after every FOMC meeting began in 1994. Over the 1990-94 period, financial markets inferred the size and direction of the target federal funds rate based on open market operations conducted at 11:30am on the first business day after the FOMC meeting. In addition, on some occasions, a press release regarding discount rate changes was issued prior to an FOMC meeting. In these situations, financial market participants correctly inferred a change in the federal funds rate as well.

Figure A1 shows the actual changes in the target federal funds rate as well as the exogenous shocks used in our baseline representation in this paper. The dashed line depicts the actual change in the target federal funds rate while the solid line represents the high-frequency shocks as described above. The identified shocks are small but not insignificant. The average high-frequency shock over the 1990-2008 sample is about zero with a standard deviation of 11 basis points. Approximately 40% of shocks were contractionary while 60% are expansionary, and there are 70% more shocks than actual changes in the federal funds rate.

2 Robustness

We consider a number of robustness checks to our baseline specification in this section.

2.1 Wide Age Bins

In our baseline specification, we estimate separate regressions for each five-year age bin. This allows the coefficients on the fixed effects and the other regressors to change with each specification. It also does not take into account that an increase in the proportion of the population in one age group is likely a reduction in another age group. For both of these reasons, it is of interest to include all of the interaction terms in a single regression. As it is not practical to run a single

Figure A1: Federal Funds Rate Changes and Shocks

Basis points

— Quarterly aggregated high-frequency shock   ---- Actual change in federal funds rate
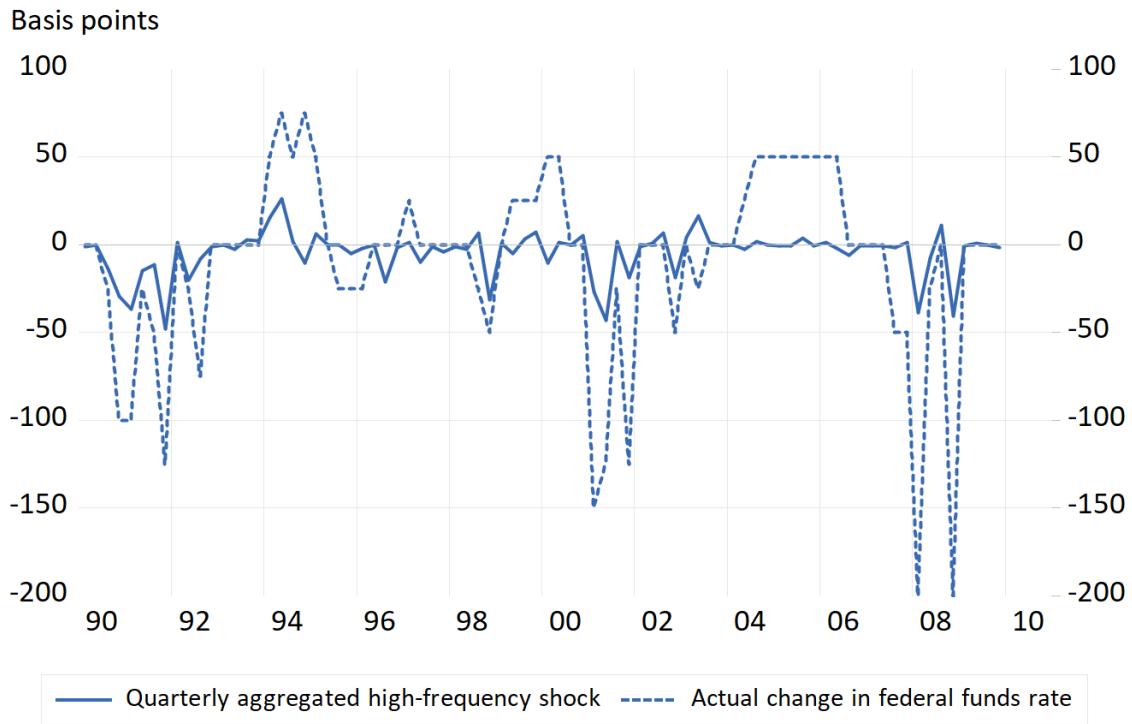
regression that includes all of the age bins as regressors, we instead aggregate the age bins into three broad categories: 20-39, 40-59, and 60+. In this we are motivated by our finding that there are in essence three important age groups.

The results appear in the top panels of Figure A2. The pattern is the same as in our baseline specification: A greater proportion of the young dampens the effects of a monetary policy shock and a greater proportion of the middle aged amplifies these effects. There is also weak evidence that a greater proportion of the old dampens the effects of monetary policy.

We also tried running a single regression with ten-year age bins: 20-29, 30-39, 40-49, 50-59, and 60+. The results appear in the bottom panels of Figure A2. Again they are broadly consistent with our baseline specification, although the estimates for the 20-29 and 50-59 bins are small and insignificant in this specification. The strongest effects are for the 30-39 and the 40-49 age bins.
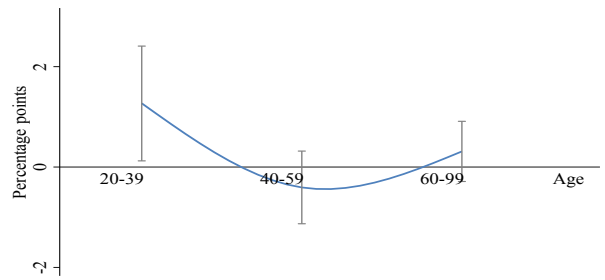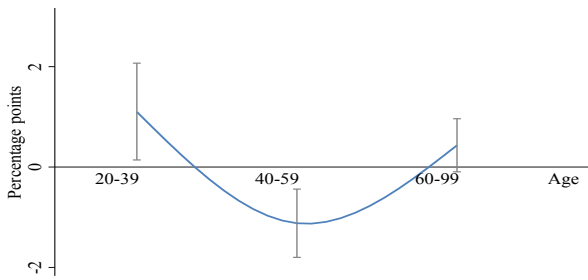
Figure A2: Wide Age Bins, Estimated Simultaneously
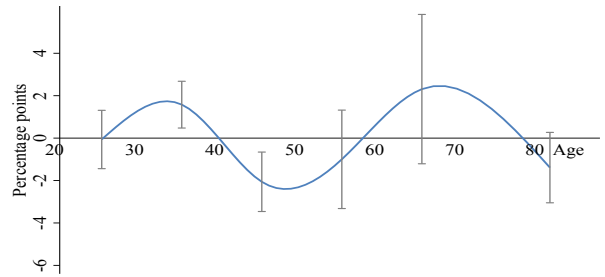
PERSONAL INCOME
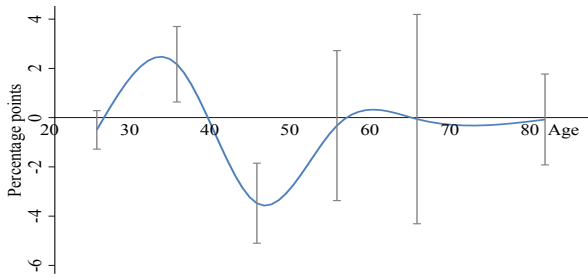
PRIVATE EMPLOYMENT

Three bins: Young, Middle, Old

Three Bins: Young, Middle, Old

10-year Age Bins

10-year Age Bins

The horizontal axis represents the age groups a. The vertical axis represents the effect on the dependent variable of a positive one percentage point shock to the federal funds rate interacted with a one percentage point increase in the population share of group a. The solid line represents the point estimates. The vertical bars represent the 95% confidence intervals given Driscoll-Kraay standard errors.

2.2 Aggregation to BEA Regions and Elimination of Small States

We test the robustness of our results to borders and to the level of aggregation. One of the main differences between states and nations is that the borders of states tend to be more porous. It is therefore of interest to see if reducing the importance of borders affects our results. We run two experiments. First, we aggregate states up to the level of BEA regions. This reduces the flow of people and goods into and out of the region as much of what was interregional trade and migration becomes intraregional. Second, we eliminate states with small populations, namely Alaska, North Dakota, Vermont, Washington D.C., and Wyoming. Migration may have a larger effect on these states.

Figure A3 presents the results. Aggregating to the 8 BEA regions leads to stronger, but less precise estimates. Aggregation reduces the degrees of freedom and hence the statistical significance of our results. The basic pattern of young, middle aged and old remains. Dropping the small states has little effect on either the economic or statistical significance of our results.

2.3 Subsample stability

Federal funds futures markets began operating only in the late-1980's, which limits the extent of subsample stability that we can conduct using the high-frequency shocks. In addition, quarterly employment data is available at the state level beginning only in 1990. We compare our baseline results to two subsamples. First, we truncate all data in 2006 to avoid any contamination with the housing market crash and the Great Recession. Second, we begin our sample in 1995, after the FOMC began issuing press releases following every FOMC meeting.

Figure A4 illustrates the effects on personal income and private employment in each of the subsamples. For ease of comparison, the first row contains our baseline results for the 1990-2008 sample period. The main story is largely unchanged for the different sample periods. Truncating the data in 2006 implies slightly weaker effects on both personal income and private employment than if we include the later period.

Beginning the estimation in 1995 exaggerates (amplifies) the demographic cycle for personal income. The dampening effect of the young and the stronger effect of the middle ages are both
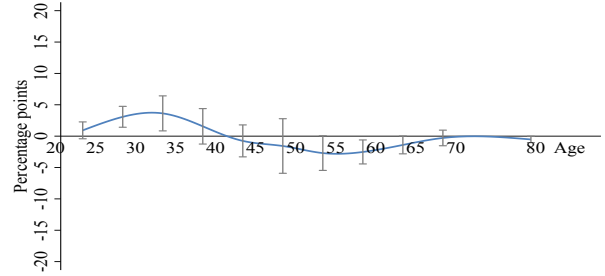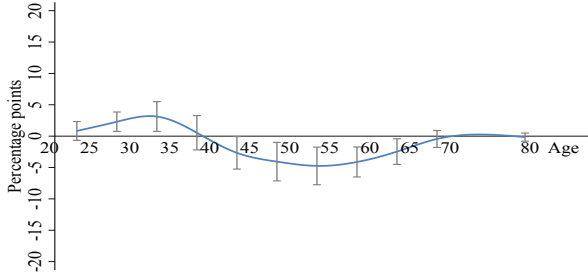
Figure A3: BEA Regions and Eliminate Small States
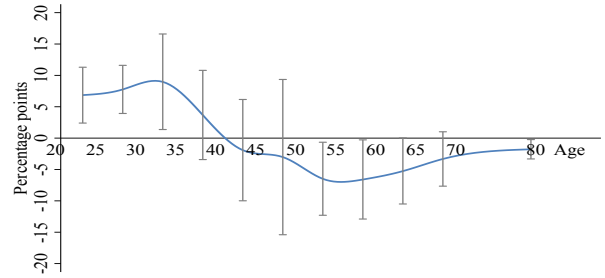
Personal Income

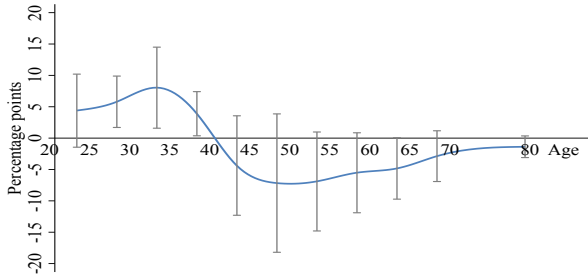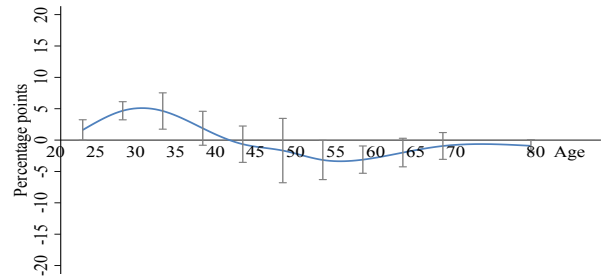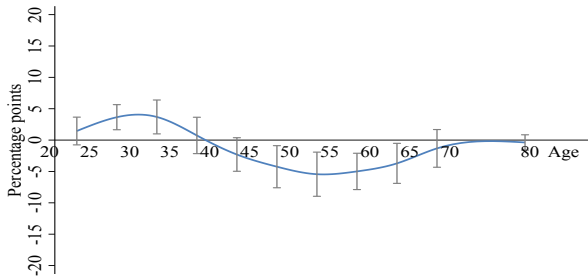**Private employment**

Baseline

Baseline

BEA regions

BEA regions

Drop Smallest Five States

Drop Smallest Five States

The horizontal axis represents the age groups a. The vertical axis represents the effect on the dependent variable of a positive one percentage point shock to the federal funds rate interacted with a one percentage point increase in the population share of group a. The solid line represents the point estimates. The vertical bars represent the 95% confidence intervals given Driscoll-Kraay standard errors.
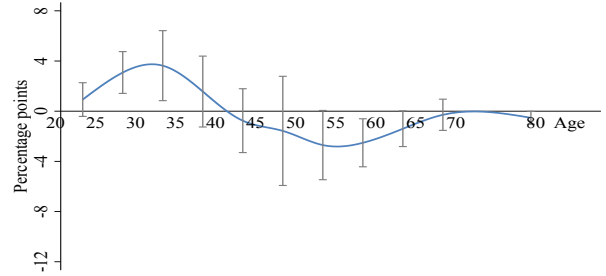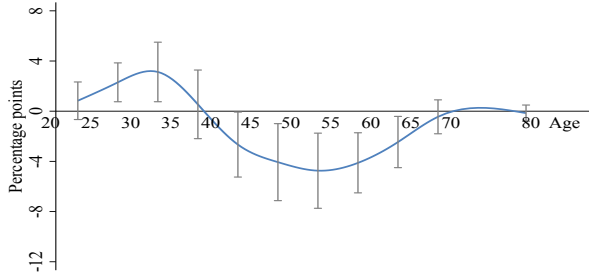
Figure A4: Subsample Stability

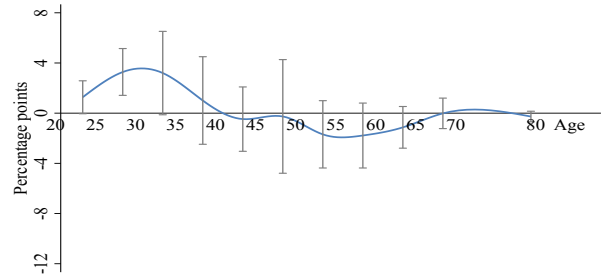**Personal Income**
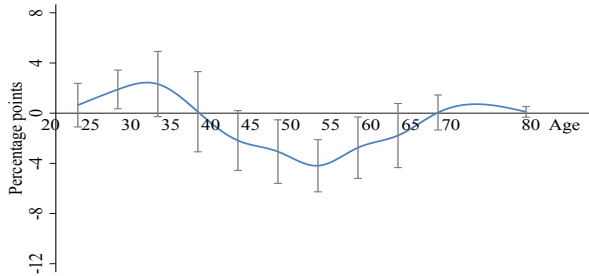
Private employment

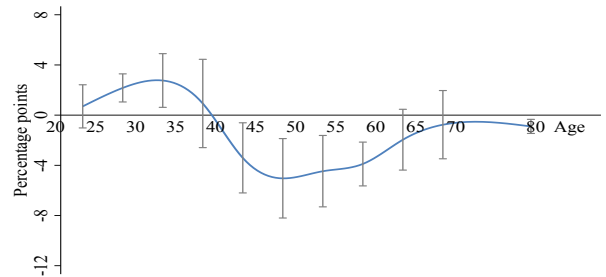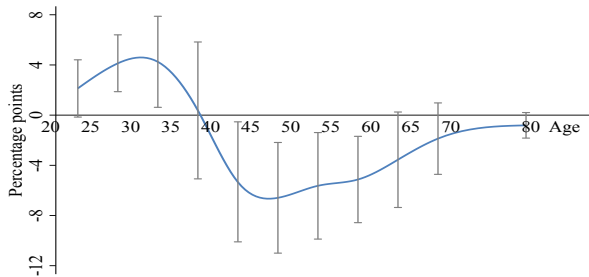1990-2008 (Baseline)

1990-2008 (Baseline)

1990-2006

1990-2006

1995-2008

1995-2008

The horizontal axis represents the age groups a. The vertical axis represents the effect on the dependent variable of a positive one percentage point shock to the federal funds rate interacted with a one percentage point increase in the population share of group a. The solid line represents the point estimates. The vertical bars represent the 95% confidence intervals given Driscoll-Kraay standard errors.

amplified in the 1995-2008 sample period as compared to our baseline results. For private employment, the effects from the younger age groups is smaller, but the effects stemming from the middle aged groups is even larger. Statistical significance improves for both variables if we begin the sample in 1995.

3   State Characteristics

It is possible that age is simply picking up the effect of some other state characteristics. To control for state characteristics, we extend equation (1) in the paper by interacting control variables with the monetary policy shock,

$$\Delta log[X_{s,t+i}] = \alpha^{i,a}\epsilon_t^m p_{s,t}^a + \phi^{a,0} p_{s,t}^a + \beta^1 Z_{s,t}^1 + \beta^2 \epsilon_t^m Z_{s,t}^2 + \gamma_s + \delta_t + u_{s,t}. \tag{A1}$$
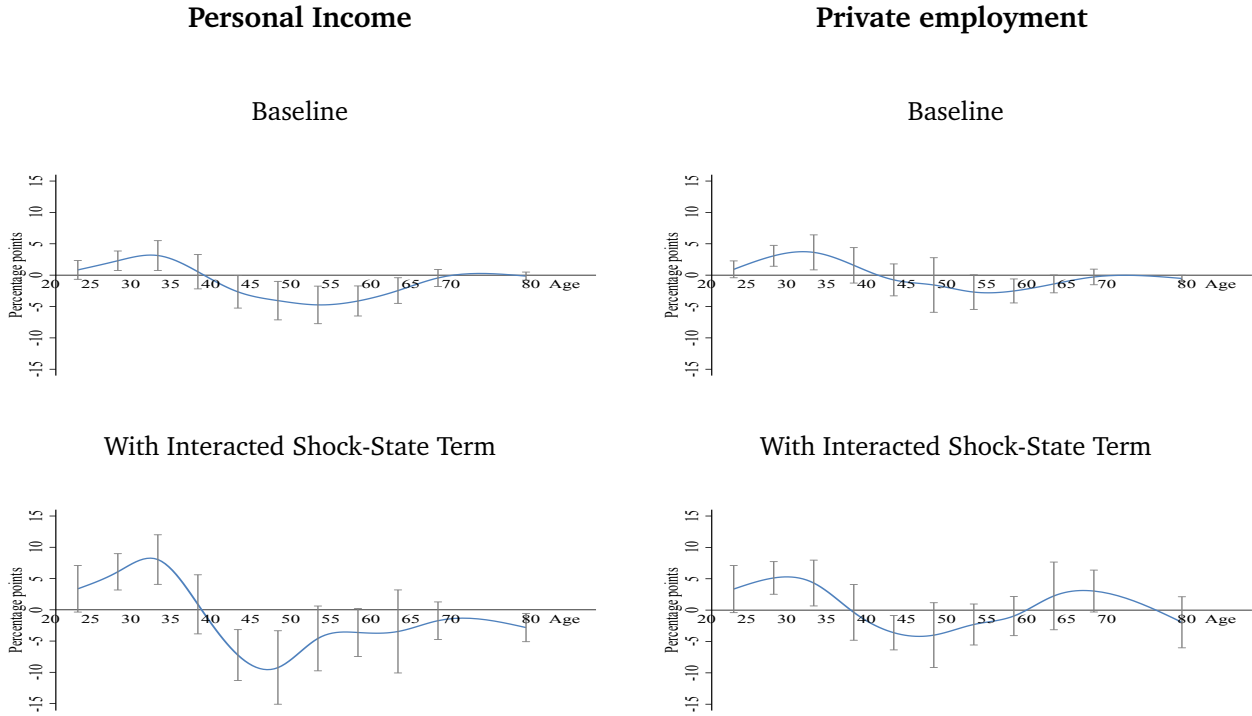
where $Z_{s,t}^1$ and refer $Z_{s,t}^2$ to control variables, such as the fraction of manufacturing or construction employment, or percentage of employees with college degrees. We consider one additional control variable at a time. All regression include lagged population growth among the $Z_{s,t}^1$.

Our first experiment is to take $Z_{s,t}^2$ to be the state fixed effect, this will control for level differences in population across states that might be correlated with fixed state characteristics.[1] For example, Southern states may have more old and young but less industry. Figure A5, shows the results for this specification. The basic pattern is the same, although there is weak evidence that a greater fraction of older people may reduce the responsiveness of employment.

Interacting the shock with state fixed effects controls for a correlation between average population in the state and average characteristics of the state. The possibility remains that some characteristics may change over time in ways correlated with the change in demographic structure. We investigate a few possibilities. Figure A6 shows the results of including the fraction of sector employment to total private employment for manufacturing, finance, and construction in both $Z_{s,t}^1$ and $Z_{s,t}^2$, that is both the fraction of employment and the fraction interacted with the monetary policy shock. These additional regressors have little impact on the coefficients $\alpha^{i,a}$. In the case of construction, the results become stronger.

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[1]Since we include state fixed effects (γ_s) in the regression, we only include Z_s interacted with the shock in this case.

Figure A5: Include Shock Interacted With State

Personal Income

Baseline

With Interacted Shock-State Term

Private employment

Baseline

With Interacted Shock-State Term

The horizontal axis represents the age groups. For a one-percentage point unexpected increase in the federal funds rate, the blue line represents the point estimates of the effect of a one-percentage point increase in the population share of group a on the growth rate of the variable of interest. Positive point estimates imply that, relative to the aggregate effects, the effects of monetary policy are weaker. Negative estimates imply stronger effects of monetary policy, relative to the aggregate effect. The vertical lines represent the 95% confidence intervals for the estimated coefficients.

Next, we control for the state income by including state personal income in both in both $Z_{s,t}^1$ and $Z_{s,t}^2$ in equation (A1). Interacting the shock with state personal income controls for differences in average income levels across states that might be correlated with the population structure. For example, incomes are lower for the young and old and higher for the middle aged. Figure A7 shows that controlling for the differences in incomes across states has a negligible impact on our results.

Wong (2019) finds that the consumption of young homeowners respond more strongly to monetary policy shocks. To understand whether the housing market is driving our results, we control for house prices, home ownership rates, and the fraction of mortgages that are adjustable-rate mortgages (ARMs) by adding these variables one by one to both $Z_{s,t}^1$ and $Z_{s,t}^2$. The results of this estimation are shown in Figure A8. The basic pattern survives.
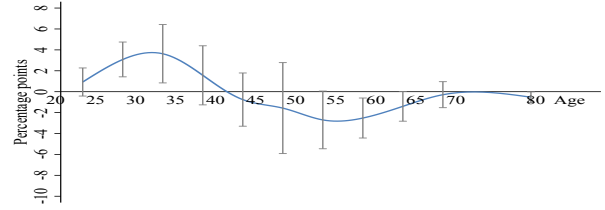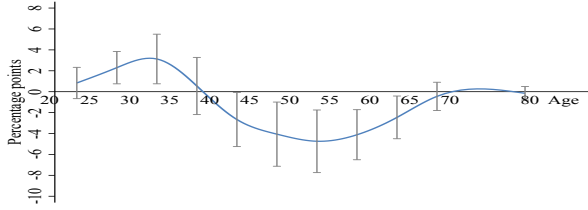
Figure A6: Control for Share of Employment in Other Sectors
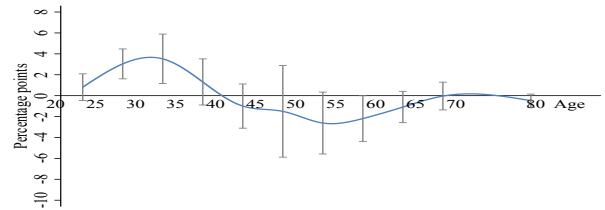
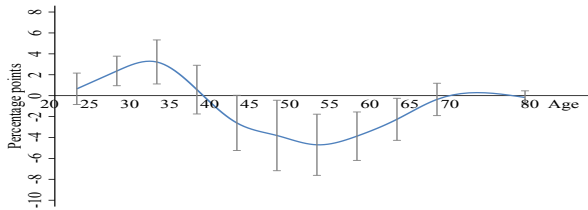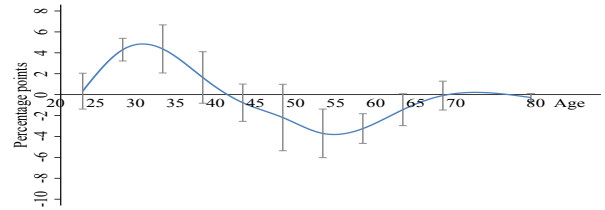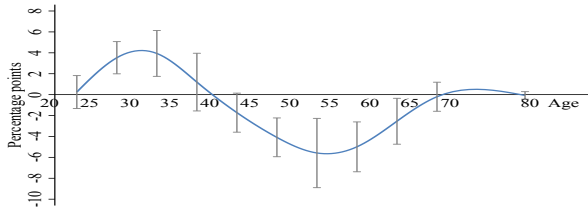**Personal Income** **Private Employment**

Baseline

Baseline

Share of Manufacturing Employment

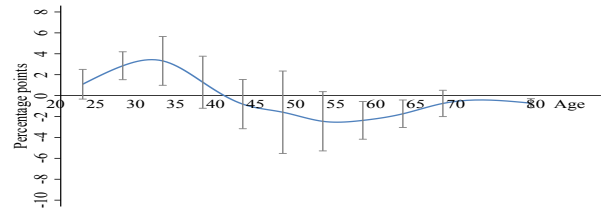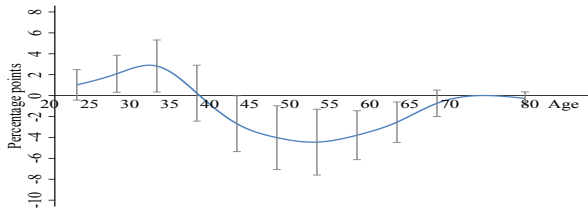Share of Manufacturing Employment

Share of Construction Employment

Share of Construction Employment

Share of Financial Activities Employment

Share of Financial Activities Employment

The horizontal axis represents the age groups a. The vertical axis represents the effect on the dependent variable of a positive one percentage point shock to the federal funds rate interacted with a one percentage point increase in the population share of group a. The solid line represents the point estimates. The vertical bars represent the 95% confidence intervals given Driscoll-Kraay standard errors.

Figure A7: Control for State Personal Income (Interacted with the Shock)
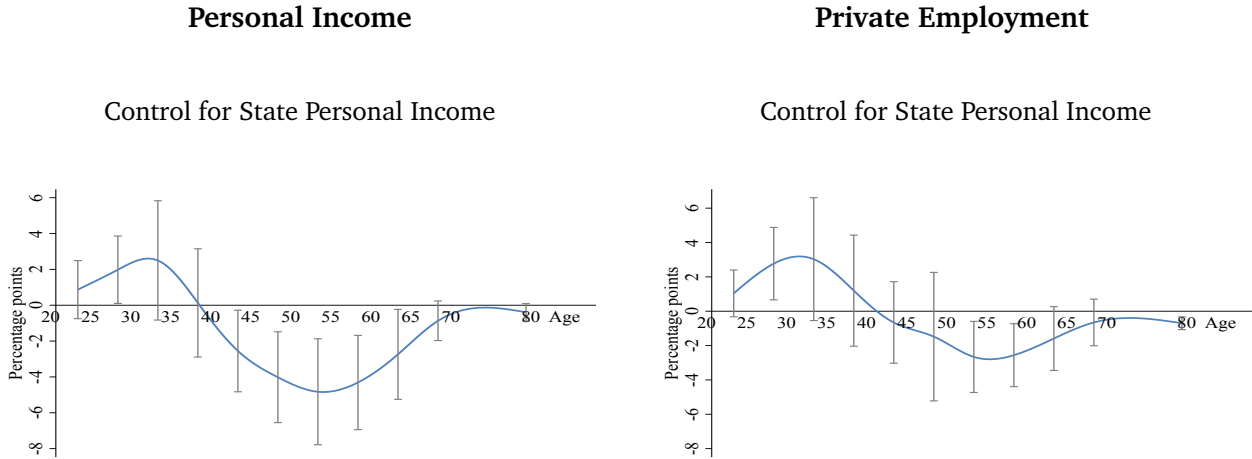
Personal Income   **Private Employment**

Control for State Personal Income   Control for State Personal Income

The horizontal axis represents the age groups a. The vertical axis represents the effect on the dependent variable of a positive one percentage point shock to the federal funds rate interacted with a one percentage point increase in the population share of group a. The solid line represents the point estimates. The vertical bars represent the 95% confidence intervals given Driscoll-Kraay standard errors.

What else might age be proxying for? To separate out the effects of age from other demographic characteristics of states, we consider the percentage of employees who have college degrees, or are white, or are male. The data is from the LEHD. Interacting these characteristics with the monetary shocks allows us to separate out the responsiveness of these groups in the population to monetary policy. For example, if college educated workers are more informed about changes in and the effects of monetary policy, these workers might respond more to shocks relative to workers without college degrees. After controlling for this effect, the effects of the age distribution might disappear. Figure A9 presents the results from adding the various demographic variables to both $Z_{s,t}^1$ and $Z_{s,t}^2$. We also include the baseline results and the baseline regression estimated on the LEHD sample.[2] The difference from the baseline arises mainly from a change in sample. Including education has little effect. The results controlling for sex and race are almost exactly the same as the results for education. We conclude that obtaining a college degree, sex, and race are not driving our results.[3]

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[2]The sample size for the baseline results is 3825 observations for 51 states. The sample size for the regressions controlling for demographic variables is 2324 observations for 50 states.

[3]Leahy and Thapar (2021) investigate whether the impact of monetary policy shocks depends on these demographic characteristics.
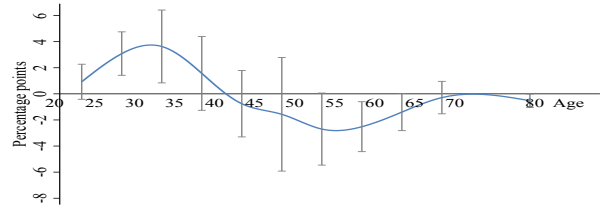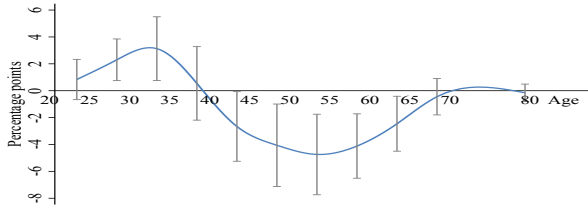
Figure A8: Control for Housing Related State-Level Characteristics

Personal Income   **Private employment**
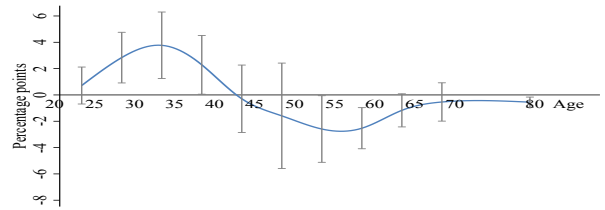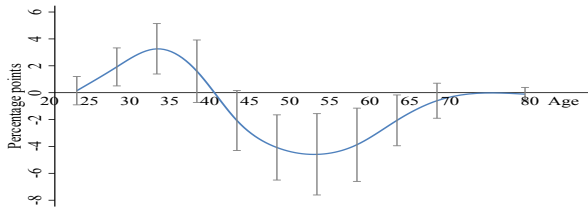
Baseline   Baseline
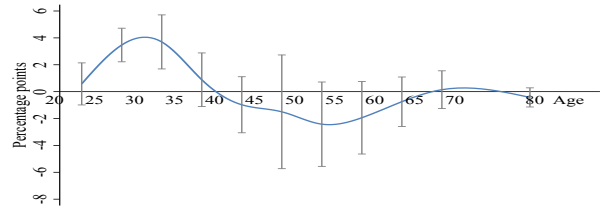

House Prices   House Prices

Homeownership Rates   Homeownership Rates
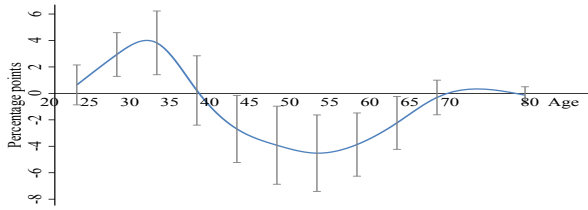
ARM Fraction   ARM Fraction
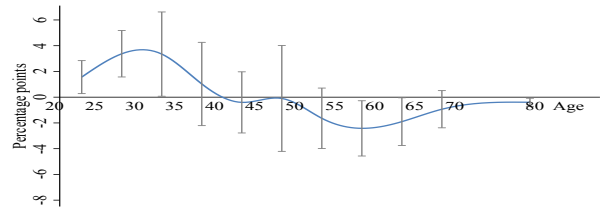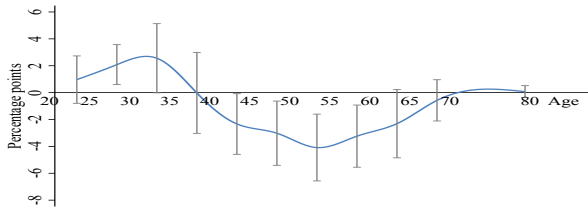
The horizontal axis represents the age groups a. The vertical axis represents the effect on the dependent variable of a positive one percentage point shock to the federal funds rate interacted with a one percentage point increase in the population share of group a. The solid line represents the point estimates. The vertical bars represent the 95% confidence intervals given Driscoll-Kraay standard errors.

Figure A9: Control for Other Demographic Characteristics

Personal Income	**Private employment**

Baseline

Baseline

Baseline Using LEHD sample

Baseline Using LEHD sample
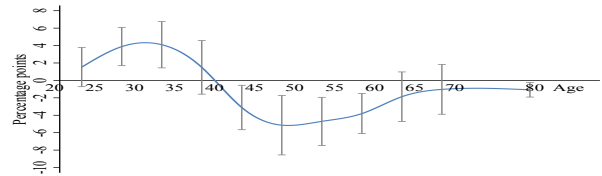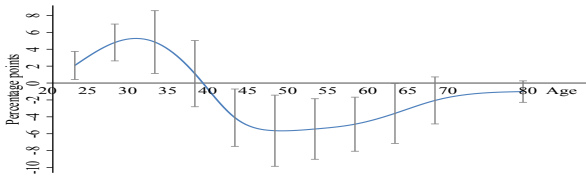
Education

Education
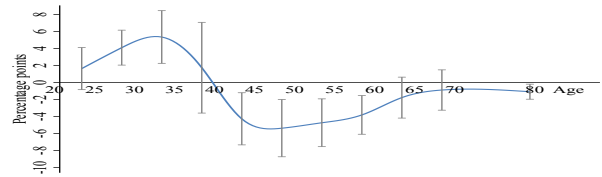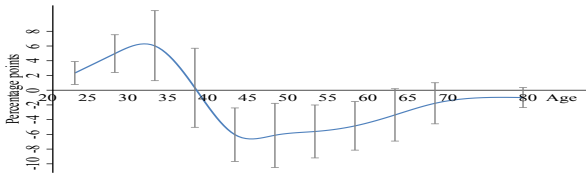
Race

Race
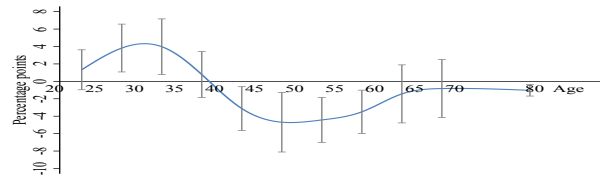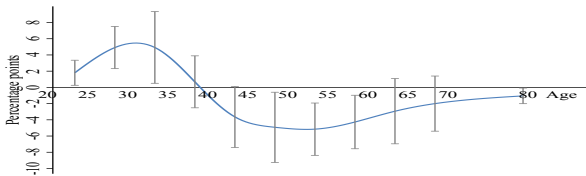
Gender

Gender

The horizontal axis represents the age groups a. The vertical axis represents the effect on the dependent variable of a positive one percentage point shock to the federal funds rate interacted with a one percentage point increase in the population share of group a. The solid line represents the point estimates. The vertical bars represent the 95% confidence intervals given Driscoll-Kraay standard errors.
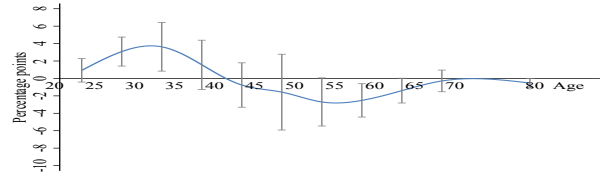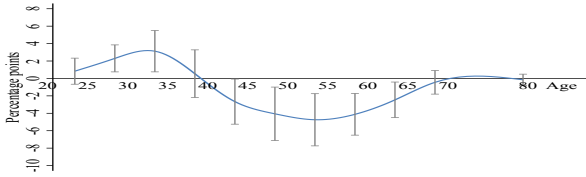
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4 Firm Age and Size

It is possible that the demographic structure of the state is correlated with the distribution of firm sizes or ages. In this section we show that the effect of age structure on monetary policy survives when controlling for these characteristics.

Figure A10 graphs the effect of an increase in the fraction of the population in age bin a on the impact of monetary policy after six quarters, $\alpha^{6,a}$, after controlling for the share of young firms and small business. The dependent variable in the left panels is personal income. In the right panels it is private employment. In the top panels, we add the fraction of firms that are $0-5$ years old to both $Z_{s,t}^1$ and $Z_{s,t}^2$ in equation (A1). In the bottom panels, we include the fraction of firms with 249 or fewer employees to both $Z_{s,t}^1$ and $Z_{s,t}^2$. The pattern seen throughout the paper survives, indicating that a correlation between the demographic structure and young and small businesses is not driving our results. The share of middle aged does not appear to be proxying for the share of either young or small businesses in total employment.

Figure A10: Controlling for the Effect of Young and Small Firms

Personal Income

Control for fraction of young firms

Private Employment

Control for fraction of young firms

Control for fraction of small firms

Control for fraction of small firms
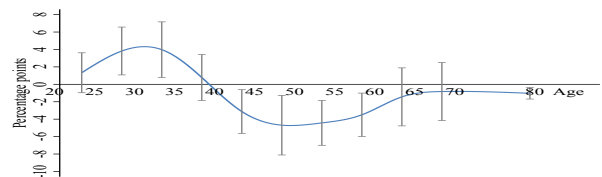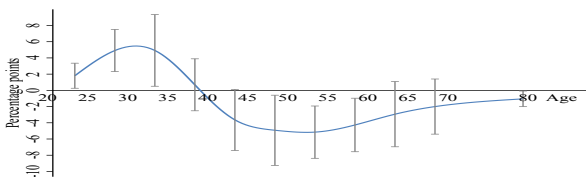
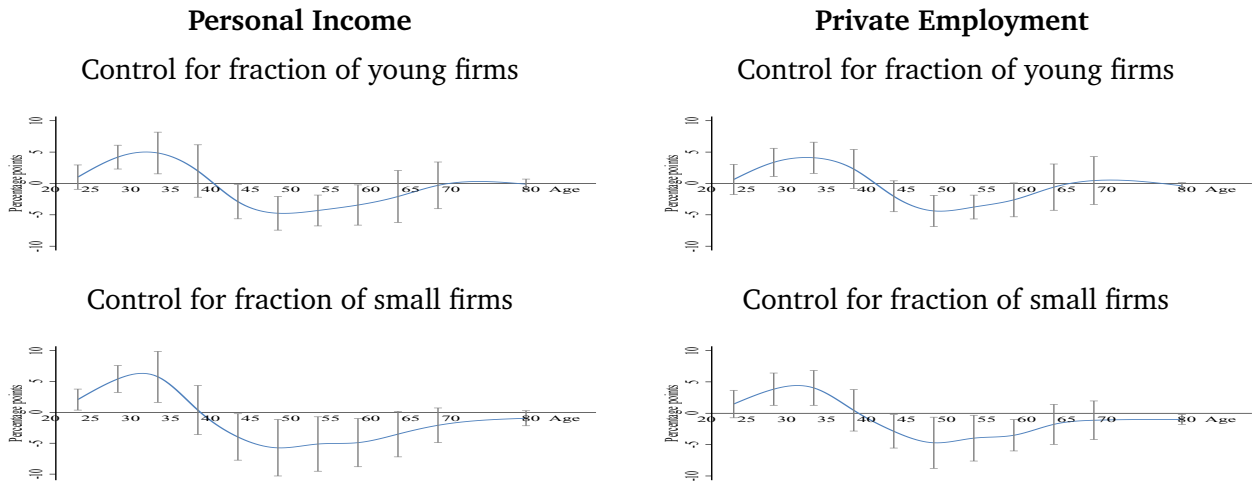The horizontal axis represents the age groups a. The vertical axis represents the effect on the dependent variable of a positive one percentage point shock to the federal funds rate interacted with a one percentage point increase in the population share of group a. The solid line represents the point estimates. The vertical bars represent 95% confidence intervals given Driscoll-Kraay standard errors.

5 Data Appendix

5.1 State-Level Data

Table 1 lists all the state-level data used in the paper as well as the frequency and the source of the data. For annual data, we do not interpolated the data and assume that the variable does not change over the calendar year. For monthly employment series, we use the quarterly average in this paper. Exceptions are noted in the footnotes below the table.

Table 1: State Level Data

	Series	Frequency	Source	Sample Used
	MAIN SERIES (SA)			
1.	Personal income	Quarterly	BEA	$1980 - 2008$
2.	Private employment	Monthly	BLS	$1990 - 2008$
3.	Population by age	Annual	Census	$1980 - 2008$
4.	Total population	Annual	Census (from FRED)	$1980 - 2008$
	STATE INCOMES (SA)			
4.	Proprietors income	Quarterly	BEA	$1990 - 2008$
5.	Wage and salary income	Quarterly	BEA	$1990 - 2008$
6.	Dividend, interest, and rental income	Quarterly	BEA	$1990 - 2008$
	EMPLOYMENT BY SECTOR (SA)			
7.	Manufacturing employment	Monthly	BLS	$1990 - 2008$
8.	Construction employment [a]	Monthly	BLS	$1990 - 2008$
9.	Financial activities employment	Monthly	BLS	$1990 - 2008$
	HOUSING (SA)			
10.	House prices (SA index)	Quarterly	FHFA	$1991 - 2008$
11.	Home ownership rate	Annual	Census	$1990 - 2008$
12.	ARM fraction	Annual	FHFA	$1990 - 2008$
	EARNINGS, EMPLOYMENT, AND PAYROLL (NSA)- LEHD [b]			
13.	By age of employees	Quarterly	Census	$1990 - 2008$
14.	By educational attainment of employees	Quarterly	Census	$1990 - 2008$
15.	By race of employees	Quarterly	Census	$1990 - 2008$
16.	By gender of employees	Quarterly	Census	$1990 - 2008$
17.	By size of firm	Quarterly	Census	$1990 - 2008$
18.	By age of firm	Quarterly	Census	$1990 - 2008$
19.	Tradable and non-tradable industries	Quarterly	Census	$1990 - 2008$
	BUSINESS FORMATION (SA) [c]			
20.	Establishment births	Quarterly	BLS	$1992 - 2008$
21.	Establishment deaths	Quarterly	BLS	$1992 - 2008$

a. Construction employment is available for only 44 states. Data for Delaware, Washington DC, Hawaii, Maryland, Nebraska, South Dakota, and Tennessee are not included.

b. The LEHD dataset is an unbalanced panel. States were added at different times. Massachusetts is not in our dataset, since they were added to the panel beginning in 2010.

c. Establishment births and deaths data begins only in 2000 for Washington, D.C.

Population $(3-4)$**:** To construct the fraction of the population in each age bin we use historical Census data obtained directly from the Census' FTP site. As the aggregated data from this site has

a jump in the year 2000, we use the Census' total population series obtained via the St. Louis Fed's FRED data portal to construct each state's population growth rate, which we use as a control variable in our estimation.

Seasonal Adjustment of LEHD Data $(13 - 18)$**:** Detailed payroll, employment, and earnings data from the Quarterly Workforce Indicators dataset, which is part of the Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) program, is not seasonally adjusted. We use the Census Bureau's X13 program for R/EViews to seasonally adjust each series by state.

Seasonal Adjustment of LEHD Data (19)**:** We use the LEHD data set to construct series of total payrolls of tradable and non-tradable industries using four-digit NAICS industry level data. We follow the classification of tradable vs non-tradable industries used by Mian and Sufi (2014). To seasonally adjust the data, we first aggregate the payrolls of all the four-digit industries categorized as tradable and non-tradable, respectively. We then seasonally adjust each series by state.[4]

5.2   U.S. Data

All national U.S. data used in the paper, along with the source of the data, are listed below. We use data beginning in 1960 to estimate the structural shocks from a VAR.

Table 2: U.S. Data

	Series	Source	Sample Used
1.	Real GDP	FRED at the Federal Reserve Bank of St. Louis	$1960 - 2008$
2.	CPI	FRED at the Federal Reserve Bank of St. Louis	$1960 - 2008$
3.	CRB commodity price index	Haver Analytics	$1960 - 2008$
4.	Unemployment rate	FRED at the Federal Reserve Bank of St. Louis	$1990 - 2008$
5.	Private employment	FRED at the Federal Reserve Bank of St. Louis	$1990 - 2008$
6.	Personal income	FRED at the Federal Reserve Bank of St. Louis	$1990 - 2008$
7.	Federal funds rate	FRED at the Federal Reserve Bank of St. Louis	$1960 - 2008$
8.	High-frequency shocks	Ottonello and Winberry (2020)	$1990 - 2008$
9.	Romer and Romer shocks	Ramey (2016)	$1980 - 2007$

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[4]Seasonally adjusting each four-digit industry and then aggregating, unfortunately, was not feasible since data for many industries is significantly distorted (fuzzed values are released) to maintain confidentiality. In addition, some data was missing for a few quarters in some cases or payroll data was zero in certain quarters. Due to these data constraints, we decided to aggregate the data first and then seasonally adjust.

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