Economic Uncertainty's Impact on Employment Fluctuations: Estimating the Importance of the Age Distribution

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Abstract

This paper provides evidence that the economic impact of changes in aggregate uncertainty depends on the population's age distribution. The volatility in employment due to uncertainty is lower in US states with a higher population of prime-aged workers. This finding comes from a series of regressions using quarterly state panel data from 2000 to 2017. To address potential endogeneity, the current age distribution is instrumented by past birth rates, and the state-level uncertainty is instrumented by national uncertainty. Regression estimates indicate a quantitatively significant reduction in employment volatility for states with a higher share of prime-age workers. The results are robust across a battery of approaches, including using alternative variable definitions and model specifications, analyzing various state-level control factors, examining dynamics using local projections, and considering labor fluctuations in job gains and losses, unemployment, and participation volatilities.

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1 Introduction

This paper provides empirical evidence indicating that US states with a larger share of prime-aged workers are significantly less sensitive to economic uncertainty and therefore suffer less employment volatility. This finding comes from a series of regressions using a quarterly panel of US state data from 2000 to 2017. To address potential endogeneity concerns, the current age distribution is instrumented with past birth rates and state economic policy uncertainty is instrumented using national policy uncertainty.

Two factors motivate this research. First, the US population is rapidly aging (Berg et al. (2021); Maestas, Mullen, and Powell (2023)). Figure 1 shows the decline in the proportion of prime-aged workers (25-54 years) relative to the total working-age population (15-64 years) from 2001 to 2017. In contrast, Figure 2 reveals an increasing share of older working workers (aged 55-64). The aging trend will continue to affect the economy for the foreseeable future. Note, however, that the aging patterns are not uniform across states. The empirical strategy below leverages these demographic differences.

The second motivating factor comes from the growing body of research showing that the uncertainty changes around future aggregate economic indicators have tangible effects on the macroeconomy. These effects manifest in various aspects, including GDP growth, inflation rates, and labor-market outcomes (Baker, Bloom, and Davis (2012); Bloom (2009); Bloom (2014)). While the subsequent section provides a comprehensive review of the relevant literature, it is worth noting that several studies have provided compelling evidence of uncertainty's detrimental impact on economic activity, particularly during the 2008 global financial crisis and the recent global pandemic of 2020.

Importantly, both economic uncertainty and population aging exhibit variation across states, Given that these two factors - age distribution and aggregate uncertainty - have independently been linked to economic volatility. A natural next step is to examine whether there is an interrelationship between uncertainty and age distribution within the context of business cycles. The analysis that follows shows such a relationship, particularly for employment volatility. This interaction is important for understanding how the aging population and uncertainty changes affect economic fluctuations.

This study analyzes the impact of the interaction between uncertainty and age distribution on employment volatility across U.S. states, utilizing quarterly data from 2000Q1 to 2017Q4. The empirical analysis employs instrumented regressions (IV) and instrumental local projections (LP-IV) to assess the effects of age distribution, economic uncertainty, and their interaction on employment volatility, with primary focus on the coefficients of uncertainty and the interaction term. Employment volatility is measured using the standard deviation of employment within various rolling windows of quarterly observations. This approach provides a dynamic view of employment fluctuations over time, rather than a static snapshot.

Separate regressions on employment volatility are conducted for prime-aged and older workers, while the baseline regression incorporates both prime and young working age groups, using the older working age group as a reference. The baseline model utilizes the state-level economic policy uncertainty measure developed by Baker, Davis, and Levy (2022). For robustness, the study also considers alternative economic uncertainty measures commonly employed in the literature.

Potential endogeneity exists between age distribution, economic uncertainty, and labor-market volatility. Omitted variables, such as migration patterns, could simultaneously affect local age structures and labor-market outcomes. Moreover, state labor-market dynamics might influence state uncertainty trends rather than the reverse. To address endogeneity concerns, this study employs two instrumental variables: First, past birth rates are used as an instrument for the current working-age population, assuming that historical birth rates are not influenced by current labor-market conditions. Second, changes in national-level economic policy uncertainty (ΔEPU) serve as an instrument for state-level changes ($\Delta SEPU$). This approach assumes that national economic uncertainty affects local employment volatility primarily through its impact on state-level economic uncertainty.

The IV estimation results suggest that, following economic-policy uncertainty changes, states with a typical age structure see an increase in employment volatility: a one-percentage-point increase in the $\Delta SEPU$ corresponds to a 3.2% rise in employment volatility. However, states with a higher proportion of prime-aged workers experience less employment volatility. When comparing states with a higher share of prime-aged working population to those with a higher share of older working population, a one-percentage-point increase in $\Delta SEPU$ corresponds to only a 1.4% increase in volatility. This represents a 55% reduction from a typical age structure.

Further analysis decomposes the effects of uncertainty on employment volatility using two approaches:

examining the volatility of job gains versus job losses and comparing the volatility of unemployment versus labor-force participation. These results corroborate the main findings, indicating that states with a higher proportion of prime-aged workers experience a more significant reduction in labor market dynamics. Specifically, the drop in the volatility of job losses is more pronounced than that of job gains, and there is a greater reduction in the volatility of unemployment relative to labor force participation. The robustness of these findings is confirmed through additional analyses employing various model specifications, outcome variables, and state-level controls, including demographics, education, income, welfare policies, and political climate.

A series of local projection-IV (LP-IV) regressions demonstrates that employment volatility peaks four quarters after an increase in uncertainty. Specifically, a one-percentage-point increase in $\Delta SEPU$ leads to a 6.3% increase in volatility. However, states with a higher share of prime-aged workers experience significantly less employment volatility. When comparing states with a higher share of prime-aged workers to those with a higher share of older working-age individuals, the volatility increase is markedly less pronounced: a one-percentage-point increase in $\Delta SEPU$ is associated with only a 1.8% rise in volatility, representing a 70% reduction from the 6.3% observed in the general case. This demographic effect persists through an eight-quarter horizon, with the effect diminishing by the end of a sixteen-quarter horizon.

The remainder of the paper is structured as follows: Section 2 reviews the relevant literature and highlights how this paper fits into previous research. Section 3 discusses data sources, variable construction, and addresses identification concerns. Section 4 presents the IV regression results, emphasizing the impact of age demographics on labor-market volatility. Section 5 conducts robustness checks using alternative regression formats and incorporates various controls for the IV regression. Section 6 reports the dynamic findings using the LP-IV method. Finally, Section 7 concludes.

2 Literature Review

Previous research has explored the effect of economic uncertainty on firm investments (Baker, Bloom, and Davis (2016); Gulen and Ion (2015)), consumer spending, and saving decisions (Baker and Wurgler

(2013)), debt accumulation patterns (Malmendier and Nagel (2016)), and financial market performance (Bloom et al. (2014); Baker, Bloom, and Davis (2016)). Regarding the labor-market effects of economic uncertainty, Cacciatore and Ravenna (2021) found that increased uncertainty results in lower wages, higher unemployment rates, and lower labor-market participation, while Schaal (2017) identified the persistent effects of uncertainty on unemployment – especially for less-educated workers. Measurements of economic uncertainty vary widely, and include financial indexes (Bloom (2009)), consumer sentiment (Leduc and Liu (2016)), and economic policy (Baker, Bloom, and Davis (2012), Baker, Bloom, and Davis (2016), Baker, Davis, and Levy (2022), etc.). This paper primarily focuses on economic policy-related uncertainty from Baker, Davis, and Levy (2022), integrating other uncertainty measures from different sources for robustness checks.

Regarding the impact of economic policy uncertainty (EPU), especially on the labor market, Baker, Bloom, and Davis (2012) is one of the first papers to examine EPU. The authors constructed the EPU Index using counts of news articles referring to the economy, uncertainty, and policy. They utilized a VAR to estimate the relationship between their EPU measure and multiple economic outcomes from 1985 to 2011. The results indicated that EPU has a negative effect on labor market outcomes: employment is reduced for up to 36 months following a policy shock, bottoming out around the 12-month mark before gradually rebounding.

In their later work, Baker, Bloom, and Davis (2016) adopted a method to quantify national EPU using data from ten leading U.S. newspapers. They applied an algorithm that searches monthly for specific uncertainty terms, capturing events like the Gulf Wars and 9/11. Their findings indicate that an increase in EPU leads to a decline in essential economic indicators such as investment, employment, and output, persisting for several quarters. The negative impact is especially great in total employment, most notably in the manufacturing sector.

Gupta et al. (2018) introduced another EPU measure, using counts of terms appearing in newspapers to discuss policy unpredictability. By examining the reactions of different US regions to economic shocks, the authors identified heterogeneity in regional responses to national EPU shocks.[1] They indicated that

[1] Gupta et al. (2018) examined the role of uncertainty in business cycle volatilities in the 48 contiguous US states and the 51 largest metropolitan statistical areas (MSAs).

this variation could be attributed to distinct economic uncertainties inherent in each state affecting its business cycles. Building upon regional analyses, Baker, Davis, and Levy (2022) detected that *EPU* shocks originating in California affect its unemployment rates, with the impacts of these shocks peaking approximately one year post-shock.

Previous studies such as Berg et al. (2021) and Maestas, Mullen, and Powell (2023), which examined the impact of US demographic changes, notably the aging trend, have inspired this research. Regarding the influence of age on labor market outcomes, Jaimovich and Siu (2009) analyzed the effect of the age distribution on working hours using postwar G7 data. They found that countries with more prime-aged workers (age 30-59) had smaller business-cycle variations; young workers and older workers near retirement saw the highest work-hour volatility. Jaimovich, Pruitt, and Siu (2013) studied the age structure's influence on the labor market using CPS data from 1964 to 2010. Their results suggest that the greater work-hour volatility of young workers may be explained by differing labor preferences and technological skills.

Lugauer and Redmond (2012) identified that young workers experience greater volatility than prime-aged workers in their contribution to GDP; notably, changes in age distribution led to a 58% reduction in US business cycle fluctuations between 1977 and 2008. Additionally, Miyamoto and Yoshino (2020) found that government spending boosts output in non-aging economies, but is less effective in aging ones. Berg et al. (2021) showed that changes in the federal funds rate affect spending in older households more then younger ones, with the impact lasting over three years.

Additionally, the state-variation design draws on the insights from Gupta et al. (2018), which recommends examining the localized effects of policy uncertainty, and Maestas, Mullen, and Powell (2023), highlighting the benefits of state-based research designs for exploring the diverse impacts of US demographic changes. This paper contributes to the literature on the labor-market implications of uncertainty and demographic heterogeneity, with a focus on age-related effects across US states.

3 Data, Variables, and Identification

This section introduces the main variables and data sources and addresses identification concerns. It begins by defining the outcome variable, employment volatility, followed by various measures of economic uncertainty and their identification. Next, it details the description of different age groups and their respective identification. The section concludes with a presentation of the summary statistics.

3.1 Constructing the Outcome Variable: Employment Volatility

State employment data are from the Bureau of Labor Statistics (BLS) Quarterly Census of Employment and Wages (QCEW). Employment volatility is calculated using the standard deviation within a centered rolling window of varying quarters. The process begins with monthly employment levels from 1998Q1 to 2019Q4, which preceded the Covid-19 pandemic. Quarterly employment levels are calculated by averaging these monthly data points. The Hodrick-Prescott (HP) filter is applied with a smoothing parameter of 1,600 to isolate business cycle deviations of the employment levels from the overall employment trend. The resulting deviations represent cyclical employment levels.[2]

Following Equation 1, cyclical employment volatility for quarter t is measured by calculating the standard deviation of cyclical employment levels over a 17-quarter window centered on t. This period encompasses two years before and after t, plus an additional central quarter. This process is repeated for each quarter from 2000 to 2017, yielding 72 observations of cyclical volatility over the sample period.[3] The use of a centered rolling window for HP-filtered data in this study aligns with research such as Jaimovich and Siu (2009) and Heer, Rohrbacher, and Scharrer (2017), with the selected duration reflecting time periods referenced in prior studies.[4] To test result robustness, alternative rolling windows with varying quarter lengths and both backward and forward rolling methods are employed in subsequent checks.[5]

[2]A smoothing parameter of 1,600 is standard for quarterly data. For example, Jaimovich and Siu (2009) uses this HP filter parameter to measure cyclical volatility in response to changes in the business cycle.

[3]The original employment data extends 8 quarters beyond the final sample at both ends. The regression sample spans 2000Q1 to 2017Q4, excluding the first and last 8 quarters to account for the absence of observations in the centered 17-quarter window.

[4]Methods for constructing volatility of economic indicators vary in literature. For instance, Jaimovich and Siu (2009) use a 10-year rolling window for HP-filtered output volatility, while both Jaimovich and Siu (2009) and Lugauer and Redmond (2012) determine GDP volatility using a nine-year rolling window.

[5]Robustness checks include volatility calculations over different quarter lengths (5, 9, and 13) using a centered rolling

$$Emp\,Vol_{i,t} = [\sum_{t-8}^{t+8}(cyclical\,emp_{i,t} - \overline{cyclical\,emp_i})^2/17]^{1/2} \quad where \quad \overline{cyclical\,emp_i} = \sum_{t-8}^{t+8} cyclical\,emp_{i,t}/17, \tag{1}$$

Figure 3 depicts the evolution of cyclical employment volatility across states, focusing on 2001Q4, 2008Q4, and 2017Q4.[6] Volatility peaked during the Great Recession (2008Q4), followed by the 2001 economic recession (2001Q4), and was notably lower during the economic boom of 2017Q4. Northeastern and southwestern coastal states consistently exhibit higher volatility, while mountain states like Montana and Wyoming show lower volatility across all periods. These variations likely stem from differences in industry composition and workforce characteristics. For instance, Montana's economy, centered on agriculture and mining, employs a predominantly native-born, white workforce with below-average education levels. In contrast, The west coast of California's technology and tourism-driven economy includes 23% of the national foreign-born population, featuring greater racial and ethnic diversity. Workforces in the technology and tourism sectors tend to be more sensitive to economic recessions and uncertainties (Labor Statistics (2012)). Moreover, immigrant workers are more likely to migrate during economic uncertainties than local workers (Duzhak et al. (2021); Kochhar and Bennett (2021)).

3.2 Defining Economic Uncertainty Measures

3.2.1 State Economic Policy Uncertainty

To measure economic uncertainty, this paper incorporates several widely recognized measures from prior research. The primary measure, $\Delta SEPU$, is constructed using the equation below and represents the percentage change in the State Economic Policy Uncertainty Index (SEPU) from Baker, Davis, and Levy (2022). To construct this index, the authors analyze local news articles, discounting state-specific national papers. It comprises two facets: one that highlights local policy-driven uncertainty and the other that addresses state-level implications of national policies. This index is formulated by monthly assessments of articles with relevant keywords, calculating their proportion relative to that month's total articles. To

window, as well as evaluations using backward and forward 17-quarter rolling windows. The forward window method considers employment levels from the current quarter and the subsequent 16 quarters.

[6]The figure starts after 2000Q1 due to missing $\Delta SEPU$ data in prior years.

ensure comparability, the index is normalized using data before 2018 on the average state-level impact of national policy uncertainty. Thus, the $SEPU$ index is validated against established economic uncertainty benchmarks to assess the impact of both local policy-driven and national policies on state-level economic activities.

$$\Delta SEPU_{i,t} = (SEPU\,index_t - SEPU\,index_{t-1})/SEPU\,index_{t-1} * 100\%, \tag{2}$$

Figure 4 illustrates the evolution of $\Delta SEPU$ across states during three significant economic periods: 2001Q4, 2008Q4, and 2017Q4. These quarters coincide with notable business cycles, with varying impacts across states. During the 2001 recession, states with substantial manufacturing and computer sectors, such as Michigan and Utah, experienced increased uncertainty, depicted in darker tones. North Dakota, dominated by the crude oil sector, also saw heightened volatility.[7] The Great Recession period (2008Q4) shows widespread uncertainty, particularly in financial hubs such as Maryland and New Hampshire in the Northeast, Illinois in the Midwest, and Washington on the West Coast. By 2017Q4, following the post-Great Recession economic boom, uncertainty had markedly reduced, as indicated by lighter tones, signifying economic recovery.

3.2.2 Applying National Economic Policy Uncertainty to Address Endogeneity

The measure of state uncertainty may be endogenous to employment volatility if local newspaper search terms are influenced by local labor market volatility. This suggests that uncertainty could be driven by volatility rather than vice versa. Furthermore, unobserved factors such as state labor market policies, tax regulations, and gross product could affect both uncertainty and volatility. To address these potential endogeneity issues, I employ the change in the national economic policy uncertainty index, ΔEPU, from Baker, Bloom, and Davis (2016) as an instrumental variable for $\Delta SEPU$. As ΔEPU captures national economic uncertainty influenced by national events rather than local factors, it helps assess how national economic policy uncertainty affects state employment volatility through state-level economic policy

[7] According to Langdon, McMenamin, and Krolik (2002) and other literature, the longest postwar economic expansion in the U.S. ended in March 2001 with the onset of a recession. The manufacturing downturn began in late summer 2000 and intensified in 2001, with businesses significantly reducing spending on machinery, computers, and other capital goods.

uncertainty. A similar instrumental variable approach is used by Basso and Rachedi (2021), where national military spending serves as an instrument for state military procurement to estimate the impact of age heterogeneity on state gross product growth. The key assumption in this study is that U.S. uncertainty does not result from one state's employment volatility being higher than others.

Panel A of Figure 5 illustrates the EPU index (green line), which peaks during economic downturns such as the early 2000s recession and the Great Recession (all shaded in grey). Notable spikes are also observed during major political and economic events, including the 2010Q3 tax-cut expiration debate and the 2011Q3 debt-ceiling dispute. The blue line represents the growth rate, ΔEPU, which serves as the instrumental variable. This variable, averaging around 1.78 (marked in red), captures the rate of change in the EPU index. It notably spikes during significant political events and economic business cycles, such as the Great Recession.

3.2.3 Other Uncertainty Measures

To ensure robustness, alternative measures of economic uncertainty from various literature sources are employed. These include the percentage change in news-related policy uncertainty (ΔNPU) based on the index developed by Baker, Bloom, and Davis (2016), the percentage change in Global Economic Policy Uncertainty Index ($\Delta GEPU$) from Davis (2016), and the percentage change in financial market volatility index (ΔVIX) from the Federal Reserve Bank of St. Louis, referenced in Bloom (2009). This study also considers the change in the proxy-Baa Corporate Bond Yield (ΔBAA) from FRED, used in Choi and Loungani (2015), and the Michigan Consumer Sentiment Index (converted into percentage changes, $\Delta UMCS$) from the University of Michigan, which may reflect consumers' perceived uncertainty about the future. The latter has been employed by Leduc and Liu (2016) as a measure of consumer uncertainty. In this study, the negative of UMCS is used as an alternative proxy for consumer uncertainty to align the sign of effect with other measures. Further details regarding the construction and sources of these uncertainty indices are documented in the Appendix.

Panel B of Figure 5 plots ΔEPU alongside five other national-level measures. These measures generally exhibit unified cyclical patterns: Financial indices (ΔVIX and ΔBAA) notably peaked during the 2008 financial crisis, while news-related measures (ΔNPU) spiked during significant policy events like the 2011 debt ceiling debate. Consumers' perceived future uncertainty ($\Delta UMCS$) shows smaller variations overall. To examine the correlation among uncertainty measures, Table A.1 in the Appendix displays the variance-covariance matrix for these measures during the sample period. This table shows strong positive correlations ranging from 0.287 (between $\Delta SEPU$ and ΔBAA) to 0.946 (between ΔEPU and ΔNPU). Although the correlations vary among measures, each provides distinct uncertainty measurement resources and captures uncertainties associated with different economic activities. The subsequent regression analysis will focus primarily on $\Delta SEPU$, with results for other measures provided in the Appendix for robustness.

3.3 Constructing Population Shares

3.3.1 Age Groups

Population data is obtained from the US Census Bureau's National Population Estimate Program, which provides estimates of state resident populations for all ages based on decennial census statistics. The Bureau of Labor Statistics (BLS) defines the working-age population as individuals aged 15 to 64. This group is further divided into three age categories: young (15-24), prime (25-54), and old (55-64), expressed as shares of the total working-age population.[8] To align with the quarterly dataset and account for the gradual change in age distributions, yearly proportions are linearly interpolated into quarterly measures. The baseline regression includes young and prime-age groups, with the older working-age group omitted as the reference, to estimate the role of an aging population in the relationship between economic uncertainty and labor market fluctuations.

[8] Age group categorizations vary in literature. BLS and Berg et al. (2021) define prime age as 25-54; Lugauer (2012) as 20-54, with under 35 young; Basso and Rachedi (2021) identify 20-29 as young; Jaimovich and Siu (2009) and Lugauer and Redmond (2012) see prime age as 30-59; Jaimovich, Pruitt, and Siu (2013) define 15-29 as young and 30-64 as prime-aged; Leahy and Thapar (2019) set prime-aged at 20-35. This paper follows the definition of BLS to align with the majority of prior literature.

3.3.2 Applying Lagged birth rates to Address Endogeneity

The state age structure may be endogenous to employment volatility if working-age populations migrate in response to economic uncertainty. To address this endogeneity, this paper employs past state birth rates as instruments for the current working-age population, a method frequently used in previous studies (Shimer (2001), Lugauer (2012), Basso and Rachedi (2021), among others). Lagged peer birth rates serve as valid instruments for several reasons. Firstly, they strongly correlate with the current age structure, a connection driven by common demographic factors influencing lagged birth rates and age distribution across states. This assumption is supported by the first-stage regression results presented in Table 2. Secondly, lagged peer birth rates are likely not affected by state-level factors that influence current employment volatility, rendering them exogenous to present economic conditions. The key assumption is that lagged peer birth rates do not directly impact employment volatility other than through their effect on the current age population.

Birth data from 1936 to 2002 are obtained from various editions of the Vital Statistics PDF files from the National Center for Health Statistics. Birth rates per thousand residents were adjusted for underregistration when estimations were available.[9] Due to the unavailable birth rate data for Alaska and Hawaii before 1956, these states are excluded (following Shimer (2001); Lugauer (2012); Basso and Rachedi (2021)); therefore, the panel includes 48 states and the District of Columbia. These birth rates are used as instrumental variables for the working age group (15-64 years) from 2000 to 2017. The validity of these data is tested by cross-checking birth rates for 20-29-year-olds versus Basso and Rachedi (2021) for 2000 to 2015, showing a 99.6% correlation as in Table A.3. To calculate lagged birth rates for various age groups, the study uses a rolling average of state birth rates. For instance, the 25-54 age cohort 2000 is instrumented using average birth rates from 1946 to 1975, and for 2001, rates from 1947 to 1976 are used. This approach is applied consistently across all age groups, states, and sample periods. This hand-collected dataset contributes to the literature by extending the examined birth rate timeframe to 1936-2002. In addition, it enables a more detailed analysis of age heterogeneity, which contributes to ongoing research

[9] Prior to 1962, birth rates have two versions: one adjusted for under-registration and the other based on registered births. This study uses adjusted data from 1936 to 1962, while data from 1963 onward are based on registered births.

within the field.

3.4 Summary Statistics

Table 1 provides summary statistics for the main variables from 2000Q1 to 2017Q4. The state panel dataset comprises 3,416 observations, excluding 112 missing observations on variable $\Delta SEPU$ for certain states in the early period from 2000Q1 to 2006Q1. The dependent variable, business cycle volatility of employment, varies from 517 to just over 318,000, averaging around 26,000. This is derived from the standard deviation of cyclical employment levels, which range between -420,000 and 381,000. The primary explanatory variable, $\Delta SEPU$, measures changes in state economic policy-related uncertainty, expressed in percentage points ranging from -92 to 616 with an average of 9. Each standard deviation change in $\Delta SEPU$ corresponds to a 51 percentage-point change. This study also considers other economic uncertainty measures, with their summary statistics provided in the Appendix. Another primary explanatory variable is age groups, with shares of young (17% to 30%), prime (54% to 68%), and old (9% to 24%). Lagged birth rates corresponding to young, prime, and old age groups range from 11 to 26 ‰, 14 to 28 ‰, and 16 to 35 ‰, respectively. There is a noticeable decreasing trend in lagged birth rates from old to young, corresponding to an overall higher share of old and a lower share of prime, indicative of the US aging trend.

4 Estimating the Impact of Population Age on Uncertainty's Effect

This section investigates the relationship between state economic uncertainty and employment volatility, with a focus on the role of population age distribution. It begins by presenting the two-stage estimation specification, followed by the first-stage regression results to validate the instrumental variables. The main estimates are then presented.

4.1 Main Specification

To estimate the role of population age distribution on employment volatility impacted by economic uncertainty, a two-stage regression approach is employed. The first three equations below provide the specification for the first-stage regression with instruments, while the last equation represents the main regression specification:

First Stages:

$$D_{i,t} = \gamma_i + \alpha_1 B_{i,t-k} + \alpha_2 (B_{i,t-k} - \overline{B}) * (N_t - \overline{N}) + \alpha_3 N_t + \omega_{i,t}, \tag{3}$$

$$U_{i,t} = \gamma_i + \rho_1 N_t + \rho_2 (B_{i,t-k} - \overline{B}) * (N_t - \overline{N}) + \rho_3 B_{i,t-k} + \upsilon_{i,t}, \tag{4}$$

$$(D_{i,t} - \overline{D}) * (U_{i,t} - \overline{U}) = \gamma_i + \chi_1 (B_{i,t-k} - \overline{B}) * (N_t - \overline{N}) + \chi_2 N_t + \chi_3 B_{i,t-k} + \xi_{i,t}, \tag{5}$$

Second Stage:

$$Y_{i,t} = \gamma_i + \beta_1 U_{i,t} + \beta_2 (D_{i,t} - \overline{D}) * (U_{i,t} - \overline{U}) + \beta_3 D_{i,t} + \varepsilon_{i,t}, \tag{6}$$

where

$$\overline{D} = \sum_i \sum_t D_{i,t}/n_i n_t, \quad \overline{U} = \sum_i \sum_t U_{i,t}/n_i n_t, \quad \overline{B} = \sum_i \sum_t B_{i,t}/n_i n_t, \quad and \quad \overline{N} = \sum_t N_t/n_t$$

In Equation 3, $B_{i,t-k}$ represents the lagged birth rates in state i at time $t-k$, which instruments for the current working-age cohort, $D_{i,t}$, age group k in state i at time t. The coefficient α_1 captures the influence of these lagged birth rates. In Equation 4, N_t denotes the national ΔEPU at time t, which serve as an instrument for $U_{i,t}$, $\Delta SEPU$ in state i at time t. This relationship is captured by the coefficient ρ_1. Equation 5 describes the interaction between the differences of $D_{i,t}$ and $U_{i,t}$ from their means, which is instrumented by the interaction of the differences of $B_{i,t-k}$ and N_t from their averages for states i and time t. In each equation, γ_i accounts for state fixed effects, and other terms are included to be consistent with the second stage's structure. Note that the panel regressions do not include time-fixed effects. This is because N_t, the national ΔEPU at time t, varies only over time and captures time-specific factors common to all states.[10]

[10]The appendix provides robustness checks using a two-way fixed effects model (incorporating both time and state fixed effects).

Equation 6 represents the main regression of interest. $Y_{i,t}$ represents the business-cycle volatility of employment, defined as the standard deviation of cyclical employment in state i across a 17-quarter rolling window centered on time t.[11] The term $D_{i,t} - \overline{D}$ represents the age structure of a state relative to the sample average. In this, $D_{i,t}$ denotes the proportion of age groups within the working population of state i at time t, and $\overline{D}$ represents the sample average. $U_{i,t} - \overline{U}$ represents deviation of $\Delta SEPU$ from its average, where $\overline{U}$ represents the average value of $\Delta SEPU$ for the sample period.[12]

The regression in Equation 6 uncovers the effect of the aged population distribution on the relationship between economic uncertainty and labor market volatility. The coefficient β_1 measures the direct effect of $U_{i,t}$ on $Y_{i,t}$, while β_2 captures the interaction between the demeaned $U_{i,t}$ and demeaned $D_{i,t}$. Specifically, β_1 quantifies the impact of economic uncertainty on employment volatility when a state's age share ($D_{i,t}$) equals the sample average ($\overline{D}$). Omitting the β_2 term thus allows the influence of uncertainty on volatility solely represented through β_1. If a state's age structure differs from the national average, β_2 counts for the additional impact from each percentage point of difference. This approach indicates that the effect of economic uncertainty on volatility varies with a state's age structure, and considering deviations from the average facilitates the interpretation of the results. While β_3 incorporates $D_{i,t}$ from its interaction with $U_{i,t}$ to account for the direct effect of age structure on volatility, this is not the primary focus of the analysis.[13]

The panel structure is essential for identifying the impact of demographics on cyclical volatility driven by uncertainty. State fixed effect is used to account for time-invariant, state-specific factors like geographic and historical characteristics. The model also incorporates a time-varying and state-invariant variable, economic uncertainty N_t, to control for unobserved time-varying features common across states, including global economic trends and national policy changes. Therefore, the causal relationship is identified based on both state- and time-varying factors. To illustrate, consider the variation in working-age population distribution across states at any given time. For example, in 2000Q1, New Hampshire boasted a 68% prime

[11]Robustness checks utilize alternative windows of 5, 9, and 13 quarters, and consider backward and forward windows in addition to center. These results are presented in the Appendix.

[12]Other national uncertainty measures are also examined for robustness, including $\Delta GEPU$, ΔNPU, ΔVIX, ΔBAA, and $UMCS$. The results of these analyses are reported in the Appendix.

[13]Introducing $\overline{D}$ does not alter the estimation of the age-heterogeneous effect β_2 but enables a direct interpretation of β_1, as the change in $\Delta SEPU$ affects cyclical volatility for a state with an average age-group share ($D_{i,t} = \overline{D}$).

age population, while Utah had only 59%. Moreover, a state's relative ranking can change significantly over time. New York, for instance, ranked 38th lowest in prime age share in 2004 but climbed to the ninth highest by 2017.

4.2 Checking the Validity of the Instruments

Table 2 shows the first-stage regression results based on Equations 3, 4, and 5. Columns 1-3 correspond to Equation 3, where $D_{i,t}$ represents young, prime, and old working-age groups. Columns 4-6 present the results for Equation 4, while the remaining columns display results for the interaction terms in Equation 5. The coefficients across all columns show significance. Notably, the coefficients on birth rates (first three columns) are consistently positive and significant at the 1% level, with high F-statistics. This indicates a strong correlation between age and birth rates, confirming the validity of using lagged peer birth rates as an instrument. It is worth noting that the F-statistics show a decreasing trend from young to old. This aligns with expectations: As time passes and populations age, factors like migration and mortality create discrepancies between the state's demographic structures of older individuals and their corresponding lagged birth rates. This process gradually weakens the overall correlation between age and birth rates.

The ΔEPU coefficient in the next three columns is positive and significant at 1%. This shows a strong positive link between national ΔEPU and state $\Delta SEPU$. When national uncertainty rises (think economic downturns or debt ceiling debates), local uncertainty tends to increase correspondingly. This supports using national ΔEPU as a valid instrument for $\Delta SEPU$. The final three columns present the first-stage coefficients for the interaction between ΔEPU and three lagged birth rates for the corresponding age groups. All coefficients are significant. The coefficient for lagged young birth rates and ΔEPU is positive, while the other two are negative. These differences might stem from states with higher prime and old peer birth rates experiencing more migration flows in response to economic uncertainty, resulting in smaller shares of these age groups. Notably, the high significance levels indicate that the interaction of ΔEPU and $B_{i,t-k}$ is a valid instrument for the interaction of $\Delta SEPU$ and $D_{i,t}$. This confirms the validity of the identification for the main results that follow.

4.3 Main Results: The Role of Population Age on Uncertainty's Effect

Table 3 shows the main results from Equation 6. Newey-West autocorrelation-robust standard errors are reposted in all regressions to handle potential heteroskedasticity and autocorrelation, allowing for one year of dependence[14]. The sample spans from 2000Q1 to 2017Q4, with 3,416 observations due to early missing $\Delta SEPU$ data. The dependent variable across all columns is $Y_{i,t}$, the standard deviation of state-level cyclical employment. Independent variables include $U_{i,t}$ (growth rate of state economic policy uncertainty, $\Delta SEPU$), $D_{i,t}$ (age groups young [16-24], prime [25-54], or old [55-64] among the total working-age [15-64] population), and the interaction term $(D_{i,t} - \overline{D}) \cdot (U_{i,t} - \overline{U})$ using demeaned values. The results are obtained by instrumenting age shares with their respective lagged birth rates and $\Delta SEPU$ with national ΔEPU, while including state fixed effects. Unchecked coefficients in the table aren't the main focus of interpretation and aren't reported. In summary, the results show that states with a larger prime-aged share show significantly reduced employment volatility following economic uncertainty.

Column 1 shows the regression of employment volatility on $U_{i,t}$ ($\Delta SEPU$), $(Prime_{i,t} - \overline{Prime}) \cdot (U_{i,t} - \overline{U})$, and $Prime_{i,t}$. The $U_{i,t}$ estimate reveals that states with an average prime-aged share see increased employment volatility for each one-percentage-point rise in $\Delta SEPU$. The interaction term's estimate indicates that states with a higher-than-average prime-aged share experience significantly reduced volatility for each additional percentage point of prime-aged share, compared to states with the national average age structure. This effect is notable both statistically and economically. Column 2 shows the regression of employment volatility on $U_{i,t}$, $(Old_{i,t} - \overline{Old}) \cdot (U_{i,t} - \overline{U})$, and $Old_{i,t}$. The estimate for $U_{i,t}$ indicates that states with an average old-aged share experience increased volatility when $\Delta SEPU$ rises by one percentage point. The interaction term's estimate reveals that a higher proportion of older individuals amplifies this relationship. For each percentage point increase in the older population share, the association with employment volatility grows stronger. This effect is both statistically and economically significant.

Column 3 presents the baseline results, incorporating the prime and young age groups and their interactions with $U_{i,t}$. The old group and its $U_{i,t}$ interaction have been omitted as a reference. For states with an average age distribution, the estimate in $U_{i,t}$ suggests an increase of 86 units in employment volatility

[14] For more details, see Newey and West (1987) and Newey and West (1994).

for each increase of 1% in $\Delta SEPU$. The interaction term reveals that states with a higher proportion of prime-aged individuals experience significantly lower uncertainty-induced volatility compared to those with a larger old-age share. Each additional percentage point of prime-aged share is related to a 48-unit reduction in volatility, equivalent to a 55% decrease per percentage point increase in state economic policy uncertainty.[15]

Recall from Table 1 that the average employment volatility is 26,921, and the average $\Delta SEPU$ is 9.92. Given that the coefficient in $U_{i,t}$ is 86.94, the uncertainty elasticity of volatility is calculated to be 0.0032 (derived as $\frac{86.94}{26,921}$). This indicates that a 1% increase in $\Delta SEPU$ corresponds to a 0.0032% increase in volatility for states with an average age structure. As the average percentage change in uncertainty is 9.92%, the average increase in volatility is 0.032%.[16] The impact of uncertainty on the employment volatility may be relatively small, as many other factors contribute to this effect. The age distribution significantly influences the impact of uncertainty. States with a greater proportion of prime-aged individuals experience a reduced uncertainty-induced volatility compared to those with a larger elderly population: the effect of uncertainty decreases by 55% (calculated as $\frac{-48.38}{86.94}$).[17]

Taking into account a state with a 1.8% higher share of prime workers compared to the older working population, this would offset the impact of a 1% increase in uncertainty on the volatility of the labor market (48.38 * 1.8 = 86.94). States with a share of prime-age workers greater than 1.8% relative to the older share would experience a decrease in volatility in response to uncertainty, unlike other states where volatility increases due to uncertainty. This divergence effect is further amplified with each additional increase in the prime-to-older ratio, or with each additional percentage increase in uncertainty, which reaches more than 600 percentage points.[18] This finding suggests that the aging workforce significantly

[15]The baseline regression with alternative national economic uncertainty measures is reported in the Appendix. In general, consistent negative signs are found in the interactions.

[16]To calculate the uncertainty elasticity of volatility, the first step is to determine the percentage change in volatility for a 1% change in uncertainty, which is (86.94 / 26,921) = 0.0032. This represents the uncertainty elasticity of volatility: if the uncertainty changes by 1%, the associated volatility changes by 0.0032%. Given that the average percentage change in uncertainty is 9.92%, the average percentage change in volatility corresponds to 0.0032 * 9.92 = 0.032. In addition to the average changes, you can also consider standard changes: a one-standard deviation increase in uncertainty (51.96%) corresponds to a percentage change in uncertainty of 0.0032 * 51.96 = 0.17.

[17]This change results in an elasticity of 0.0014 (derived as $\frac{(86.94-48.38)}{26,921}$). Therefore, a 1% increase in $\Delta SEPU$ leads to only a 0. 0014% increase in volatility in states with a higher prime-age share compared to those with an older population. This change represents a reduction of 56% in elasticity (calculated as $\frac{(0.0014-0.0032)}{0.0032}$), which is considered a sizable change.

[18]This implication is supported by the average share of prime-age workers being 55% (with a maximum of 68%), while the

impacts the US labor market when faced with increasing economic uncertainty. This not only leads to increased cyclical labor market fluctuations in response to uncertainty, but it also suggests that the effect of uncertainty, resulting from workforce aging, is expected to worsen as the aging trend accelerates in the US. Aside from the main coefficient of interest, other terms in the third column, such as 'young' and its interaction term with uncertainty, are included to support the primary interpretation. These terms enable a comparison between states with a higher prime-age share and those with a larger older-age share.[19]

5 Robustness Analysis

5.1 Applying Reduced Form

This section presents robustness analyses to validate our main finding: states with a larger prime-age population exhibit a lower volatility response to economic policy uncertainty. To examine whether the relationships uncovered between age distribution and uncertainty impact are consistent without relying on instruments—and to avoid potential issues from weak instruments or violations of IV assumptions—I also conduct the reduced form regressions, excluding one or both instruments. The results are presented in Table 4.

The first three columns omit one instrument, i.e., ΔEPU is directly included as an independent variable, while the age distribution is still instrumented by the lagged birth rate. This specification is denoted as the partial reduced form. Column 1 shows a significant national uncertainty impact on local volatility, with the higher share of the prime-working age population mitigating this effect. Column 2 indicates that while national uncertainty has a positive impact on volatility, a higher share of older individuals does not show a significant effect. Column 3, the main specification of interest, mirrors the baseline regression. The results suggest that while national uncertainty significantly increases local employment volatility, states with a higher share of prime-working-age individuals relative to older workers experience a reduced impact from uncertainty. Specifically, a one-percentage-point increase in the prime-aged share changes

average share of older workers is 17% (with a minimum of less than 10%).

[19] The 'young' variable and its interaction term with uncertainty are not the primary focus of interpretation and are therefore not elaborated upon in the table. These coefficients are available on request.

the uncertainty impact on participation volatility from 0.004 (calculated as $\frac{113.3}{26,921}$) to 0.0014 (calculated as $\frac{(113.3-75.5)}{26,921}$), resulting in a 65% reduction in the uncertainty effect. Compared to the main regression, where the national-state uncertainty is used as an instrument for national uncertainty, this mitigation effect is slightly larger (65% vs. 55%).

Similar results are observed when regressing employment volatility on uncertainty and lagged birth rates as independent variables, denoted as the reduced form. Column 1 shows a significant national uncertainty impact on local volatility, with a higher share of the prime-working-age population mitigating this effect. Column 2 indicates no significant effect for a higher share of older individuals. Column 3, the main specification of interest, mirrors the baseline regression. The results suggest that a one-percentage-point increase in the prime-aged share changes the uncertainty impact on participation volatility from 0.0053 (calculated as $\frac{144}{26,921}$) to 0.0038 (calculated as $\frac{(144-42.8)}{26,921}$), resulting in a 30% reduction in the uncertainty effect, which is slightly smaller than the mitigation effect observed in the main regression (3% vs. 55%). Overall, both partial and full reduced form regressions show consistency with the findings from the main regression: age distribution plays a significant role in the impact of uncertainty.

5.2 Decomposing Employment Volatility

I further explore age impact on state employment volatility through two decomposition. The first examines how age distribution influences uncertainty's effect on job gains and losses, which together represent employment change. The second evaluates the age distribution's role in uncertainty's impact on labor force transitions (unemployment) versus labor market entry/exit (participation), as employed and unemployed individuals collectively form the labor force. As volatility in the labor market is the main research interest, each of the above labor market components has been calculated as volatilities using the same method as that for employment volatility. We then apply two-stage regressions from Equation 6 to each volatility individually. The results show that all four components experience reduced uncertainty impact in states with higher prime-aged populations. In particular, job-loss and unemployment volatilities contribute more significantly to employment volatility compared to other components.

5.2.1 Contributions of Job Gains and Losses

Job gains and losses represent positive and negative employment changes over time, respectively. Their difference equals the change in employment. To calculate job gains and losses volatility from 2000Q1 to 2017Q4, I collect data from the BLS Business Employment Dynamics (BED) statistics for 1998Q1 to 2019Q4. This complements the household survey data on labor market states (employed, unemployed, and participating). Summary statistics are in Table A.4.

$$Employ_{i,t} - Employ_{i,t-1} = Gain_{i,t} - Loss_{i,t} \tag{7}$$

$$Vol(Employ_{i,t} - Employ_{i,t-1}) = Vol(Gain_{i,t}) + Vol(Loss_{i,t}) - 2Cov(Gain_{i,t}, Loss_{i,t}) \tag{8}$$

Net employment change volatility is captured as $Vol(Employ_{i,t} - Employ_{i,t-1})$, stemming from job gains ($Vol(Gain_{i,t})$) or losses ($Vol(Loss_{i,t})$).[20] Volatilities are calculated as the standard deviation of their HP filtered levels. Excluding the covariance term for simplicity, the coefficients of the volatilities of job gains and losses should approximate the coefficient on cyclical employment volatility from Equation 6.[21] The approach of examining job gains and losses to understand labor market dynamics was initiated by Davis and Haltiwanger (1992) and has since been widely adopted in various studies. For example, Hairault, Langot, and Sopraseuth (2019) investigates the cyclical volatility of job market transition rates across age demographics with uncovering distinct volatility patterns among different age groups.

Table 5 presents the results, with the coefficients on the interaction terms being the primary focus of interpretation. Columns 1-3 show estimates for job gain volatility. Column 1 examines the effect of the prime-aged population on job gain volatility. Although the results are consistent in sign with the main findings on employment volatility, they are not statistically significant. Similarly, Column 2 reports insignificant results for the older population. Column 3, which compares states with higher shares of prime-aged versus older working-age populations, indicates that states with a larger prime-aged share experience lower volatility. Specifically, a 1% increase in uncertainty leads to a reduction in employment

[20] Hall and Jones (1999), Feyrer (2007), and Maestas, Mullen, and Powell (2023) use a similar strategy in their IV regressions, decomposing output per capita as: (GDPst/Nst = GDPst/Hoursst ×Hours$st/Lst \times L_{st}/N_{st}$).

[21] The covariance term between job gains and losses volatility is omitted due to lack of information. This issue warrants future research.

volatility by 0.0026% (calculated as $\frac{23.84}{9,067}$). Additionally, each additional percentage point increase in the prime-aged share results in a 39% reduction in the total impact of uncertainty on job loss volatility, reducing the impact to 0.0015% instead of 0.0026%.

Columns 4-6 report the estimates for job loss volatility. Column 4 shows that a higher prime-aged share significantly reduces job loss volatility. In contrast, Column 5 suggests that a higher share of older age groups increases volatility, though the results are not statistically significant. Column 6 presents significant findings when comparing states with a higher share of prime-aged individuals to those with a higher share of older populations. Specifically, a one percentage point increase in the prime-aged share changes the uncertainty impact on job loss volatility from 0.0021 (calculated as $\frac{21.6}{10,058}$) to 0.0006 (calculated as $\frac{(21.6-15.5)}{10,058}$), resulting in a 71% reduction in the uncertainty effect on job loss volatility. Both 0.0021 and 0.0006 represent the uncertainty elasticity of employment volatility, which can be interpreted as a 1% increase in economic uncertainty being associated with a 0.0021% or 0.0006% increase in local employment volatility.

The results are consistent with the main findings on labor market volatility: states with a higher proportion of prime-aged workers exhibit lower labor market volatility compared to states with a larger share of older workers. The mitigating effect of the prime-aged population on employment volatility arises from reduced volatility in both job losses and gains, with gain volatility accounting for approximately 38% (calculated as $\frac{9}{24}$) and loss volatility making up 62% (calculated as $\frac{15}{24}$). An additional robustness check, which applies the volatility of cyclical employment changes to the volatility of job gains and losses, is presented in Appendix Table A.5. These results further support the findings above.

5.2.2 Contributions of Changes in Labor Market Participation

The total labor force consists of individuals who are employed or unemployed. Thus, the volatility of cyclical employment can be attributed to two factors: the volatility of individuals transitioning between employment statuses, referred to as unemployment volatility, and the volatility of people entering and exiting the labor market, known as labor-force participation volatility. The volatilities of unemployment and participation are calculated on the basis of the standard deviations of their cyclical level measures (levels are derived from the cyclical components after applying HP filters). Data spanning from 1998Q1 to 2019Q4 is collected from the BLS Quarterly Census of Employment and Wages (QCEW), with summary statistics reported in Table A.4.

$$Employment_{i,t} = Participation_{i,t} - Unemployment_{i,t} \tag{9}$$

So that,

$$Vol(Y_{i,t}) = Vol(Participate_{i,t}) + Vol(Unemp_{i,t}) - 2Cov(Participate_{i,t}, Unemp_{i,t}) \tag{10}$$

Following the previously established approach and temporarily ignoring the covariance, the sum of the coefficients on the volatilities of unemployment and participation should equal the volatility of employment, as shown in Equation 10. Table 6 presents the estimation results. Columns 1-3 focus on unemployment volatility, while columns 4-6 estimate the volatility of labor force participation. Each column parallels the first three columns in Table 2.

The findings are consistent with the main results from the previous section: states with a higher share of prime-aged individuals experience significantly reduced volatility. Specifically, as shown in Columns 1 and 3, states with a greater share of prime-aged individuals exhibit significantly lower unemployment volatility. Column 3, which mimics the main regression, indicates that a one-percentage-point increase in the prime-aged share reduces the uncertainty impact on unemployment volatility by 50%, from 0.004 (calculated as $\frac{84.2}{21{,}190}$) to 0.002 (calculated as $\frac{(84.2-41.8)}{21{,}190}$). Both 0.004 and 0.002 can be interpreted as the uncertainty elasticity of unemployment volatility.

Columns 4-6 report the estimates for labor force participation volatility. The first two columns show no significant effect of age distribution, while the last column presents significant findings when comparing states with a higher share of prime-aged individuals to those with a higher share of older populations. Specifically, a one-percentage-point increase in the prime-aged share changes the uncertainty impact on participation volatility from 0.0008 (calculated as $\frac{15}{17{,}327}$) to 0.0001 (calculated as $\frac{(15-13.2)}{17{,}327}$), resulting in an 88% reduction in the uncertainty effect on participation volatility.

The results are consistent with the main findings on labor market volatility. The mitigating effect of the prime-aged population on employment volatility arises from reduced volatility in both unemployment and participation, with unemployment volatility accounting for approximately 76% and participation volatility making up 24%. Overall, this robustness check examines how state age structures influence economic policy-related volatility in job gains and losses, unemployment, and labor force participation. The key findings of the employment volatility decomposition are as follows. First, prime-aged individuals exhibit lower labor market volatility than the older group. Second, the reduced employment volatility mainly results from decreased job loss and unemployment volatility. However, this analysis does not consider the covariance between job gains and losses or between unemployment and labor force participation volatility, which could be explored in future research.

5.3 Regressing With Controls

5.3.1 Specification

This section incorporates various sources of variables as controls to address potential confounders that can influence the relationship between age structure and uncertainty-driven employment volatility. Variations in birth rates across states can arise from factors such as the baby boom after World War II, migration patterns, and economic growth, all of which can impact both birth rates and employment volatility. For example, states with higher migration rates typically have more diverse labor markets with a larger share of younger, highly educated migrant workers, while states experiencing high economic growth often provide more job opportunities. These factors can influence the local population's age structure and labor market fluctuations, introducing confounding effects to the regression. The omitted heterogeneity between states could violate the identification restriction, especially if it is associated with local economic uncertainty and lagged birth rates over time (Basso and Rachedi (2021)). To mitigate this, the following regressions are employed, assuming that considering these factors increases the credibility of the IV approach. The following equation represents the second stage regression with controls:

$$Y_{i,t} = \gamma_i + \lambda_1 U_{i,t} + \lambda_2 (D_{i,t} - \overline{D}) * (U_{i,t} - \overline{U}) + \lambda_3 D_{i,t} + \lambda_4 (C_{i,t} - \overline{C}) * (U_{i,t} - \overline{U}) + \lambda_5 C_{i,t} + \varepsilon_{i,t}, \tag{11}$$

where $C_{i,t}$ represents various controls, including state demographics, education, incomes, welfare policies, and the state's political climate. The primary coefficient of interest is λ_2, which shows how including these controls influence the effect of prime-age on employment volatility in response to economic uncertainty. Meanwhile, λ_4 captures the direct effect of these controls on employment volatility under economic uncertainty. The age shares ($D_{i,t}$) and national economic policy uncertainty ($U_{i,t}$) are instrumented as previously described. The rest align with the baseline regression. Summary statistics for all control variables are provided in the Appendix. The following section discusses key controls and their corresponding results.

5.3.2 Controlling State Demographics

Previous studies have used demographic controls to explore the labor market outcomes. Jaimovich, Pruitt, and Siu (2013) highlights labor market fluctuations across age groups using education and gender. Hoynes, Miller, and Schaller (2012) examines the effects of economic business cycles on different workforce segments by focusing on education and racial composition. Mennuni (2019) identifies links between a predominantly female workforce, higher education, and younger demographics with less business cycle volatility. The regression below includes demographic controls as specified earlier. Data from 2000 to 2017 is sourced from IPUMS-CPS. Consistent with previous literature, this study uses variables such as female marriage rate, racial shares, immigrant rate, weekly hours worked, and low-skilled worker share to account for the demographic influence on how prime-age share impacts employment volatility under uncertainty.

The regression results are reported in Table 7. Column 1 presents the baseline regression, while Columns 2 through 7 incorporate demographic variables such as the female marriage rate (Column 2), white share (Column 3), immigrant rate (Column 6), and Hispanic share (Column 7). Including these demographics generally reduces the magnitude of the prime-uncertainty interaction coefficient, with λ_2 changing from -48 to -43, -46, -15, and -28, respectively. This indicates that a higher share of these demographics weakens the mitigating effect of prime-age on the impact of uncertainty. In contrast, adding variables such as female workforce participation (Column 3), black share (Column 5), weekly working hours (Column 8), and low-skill share (Column 9) increases the magnitude of the coefficient on λ_2. The interaction term changes from -48 to -48, -52, -64, and -55. This suggests that a higher share of these demographics strengthens the mitigating effect of prime-age on the impact of uncertainty. Overall, the main results hold when various demographic controls are included.

5.3.3 Controlling State Income

Previous studies have analyzed how income levels and industry contributions affect economic activity. For example, Bouakez, Guillard, and Roulleau-Pasdeloup (2020) shows that sectors like construction and public infrastructure benefit more from government spending than services or finance. Similarly, Hoynes, Miller, and Schaller (2012) finds that economic cycles affect industries unevenly, with sectors like manufacturing, construction, and retail being more sensitive to downturns and experiencing greater employment fluctuations. Following the previous research, I examine the impact of state sectoral incomes. The income variables include state total personal income, total wage income, and sectoral incomes from construction, manufacturing, retail trade, transportation, and health sectors. These data are sourced from the Bureau of Economic Analysis (BEA) Regional Economic Accounts program.[22]

The regression results are reported in Table 8. When controlling for income types, the magnitude of the uncertainty-age interaction coefficient, λ_2, decreases. For example, the coefficient changes from -48 to -14 when including health income and to -39 when including manufacturing income. This suggests that states with a higher income from various sources exhibit a weaker prime share mitigating effect, though the overall results still hold. In addition to these income controls, this paper includes various other controls, such as years of education, different measures of individual income, welfare policies, and political climates with details and results in the Appendix. Importantly, the main findings remain consistent and robust across regressions, supporting the main conclusions.

6 Exploring Dynamic Responses of Employment Volatility

This section presents the dynamic empirical findings using the local projection-IV (LP-IV) method. It starts with the LP-IV specification , and then the dynamic estimation results following LP-IV are discussed.

[22]Ideally, quarterly state-level GDP data would be used, but the available datasets are limited to post-2005 data. As a substitute, state sectoral income is used as the most suitable alternative, with quarterly income levels calculated as monthly averages.

Further analysis is conducted based on the earlier two decompositions of the valotility on emplyemnt. The main finding indicates significant negative responses in employment volatility from time t to eight quaretrs after the shock $t+8$ to state economic uncertianty shock for states with higher prime share, both in terms of magnitude and duration.[23]

6.1 Specification

I employ the LP-IV framework introduced by Jordà (2005). The cumulative Impulse Response Function (IRF) regression equation is as follows:

$$\begin{aligned}Y_{i,t+h} &= \eta_i^h + \delta_1^h U_{i,t} + \delta_2^h[(D_{i,t}-\overline{D})*(U_{i,t}-\overline{U})] + \delta_3^h D_{i,t} \\ &+ \delta_4^h \sum_{s=1}^{2} U_{i,t-s} + \delta_5^h \sum_{s=1}^{2}[(D_{i,t-s}-\overline{D})*(U_{i,t-s}-\overline{U})] + \delta_6^h \sum_{s=1}^{2} Y_{i,t-s} + \omega_{i,t+h}, h = 0,1,...,H\ , \qquad (12)\end{aligned}$$

Volatility is calculated as the standard deviation of a centered 9-quarter rolling window of cyclical employment.[24] This window length differs from the previous approach, which used a 17-quarter window. The motivation for using a shorter window is related to the fact that the LP-IV estimation involves a series of IV estimates for different horizons. Hence, using a shorter window leaves a larger number of observations for estimation. Although the choice of window length may seem somewhat arbitrary, this paper aims to align closely with prior literature estimating the dynamic effect of shocks. For example, Jaimovich and Siu (2009) applied a 10-year rolling window to HP-filtered output volatility, and Lugauer and Redmond (2012) used a nine-year rolling window for GDP volatility calculations. Estimation results obtained using different centered window lengths and backward windows confirm the results are robust to different measures. For brevity, these results are relegated to the Appendix.

Explanatory variables are defined in the same manner as in the earlier two-stage equations. η_i^h captures the state fixed effect from time t to $t+h$. δ_1^h measures the effect from the current period of economic

[23]The application of two method: IV regression and the LP-IV method aligns with prior studies. For example, Imam (2015) use linear OLS and LP regressions to analyze the effects of demographic changes on the effectiveness of monetary policy.

[24]where

$$Y_{i,t} = [\sum_{t-4}^{t+4}(\Delta cyclical\ emp_{i,t} - \overline{\Delta cyclical\ emp_i})^2/9]^{1/2}, \qquad (13)$$

and

$$\overline{\Delta cyclical\ emp_i} = \sum_{t-4}^{t+4} \Delta cyclical\ emp_{i,t}/9, \qquad (14)$$

policy uncertainty from time t to $t+h$. δ_2^h reports the estimate for the interaction between the demeaned terms, $(D_{i,t} - \overline{D}) \times (U_{i,t} - \overline{U})$ from t to $t+h$. δ_3^h reports the direct demographic impact, which is not the coefficient of interest.

Following previous literature (e.g., Cloyne, Jordà, and Taylor (2020)), the regression includes two lags.[25] In addition to the two lags of uncertainty, $U_{i,t-s}$, the equation also includes two lags of the interaction, and two lags of volatility $Y_{i,t-s}$. These components account for historical variations in state employment volatility and past uncertainty. Due to the gradual and slow evolution of age structures , lagged age shares are not included. Following the previous IV strategy, $U_{i,t}$ and its lags are instrumented by the national ΔEPU measure, N_t and its associated lags. Similarly, $D_{i,t}$ is instrumented by birth rates $B_{i,t}$ to address endogeneity concerns.

The primary variables of interest are δ_1^h, which captures the direct impact of $\Delta SEPU$ on volatility, and δ_2^h, which captures the demographic effects of uncertainty-driven volatility. The sum $\delta_1^h + \delta_2^h$ represents the total effect of uncertainty on volatility considering the age share diversity. These coefficients can represent the effects of the prime or old demographic, or provide a comparison between the two. [26] Ultimately, local projections span horizons h from 0 to 8. These coefficients offer insight into how a state's working-age structure at time t influences employment volatility between horizons t and $t+8$ due to the introduction of economic policy uncertainty at time t. By including the state fixed effect and instrumenting with time varying ΔEPU, identification arises from variations both across states and over time.

6.2 LP-IV Estimation Results

Figure 6 plots the regression coefficient estimates following Equation 12, which shows the dynamic responses of employment volatility at each period for eight quarters post the economic policy uncertainty shocks. Panels a-d corresponds to the estimates for δ_1^h or δ_2^h, or their sum, $\delta_1^h + \delta_2^h$ or $\delta_1^h + n\delta_2^h$. Rows i-iii correspond to regressions with prime, old, or comparisons between the two age groups. The results are

[25] Further robustness checks with other numbers of lags will be provided in the Appendix.

[26] To be more specific, by including both prime and young in the regression and omitting old as the reference group, one can achieve this comparison.

shown with plus/minus one Newey-West standard error bands for $h = 0, 1, ..., 8$.

In Row i, a $\Delta SEPU$ shock results in a significant increase in employment volatility for states with national average age structure, peaking at four quarters after the shock (Column 1). States with a percentage point higher prime share, as shown in Column 2, experience reduced volatility, peaking at the fifth quarter post-shock. Column 3 demonstrates that the total uncertainty effect diminishes for states with more prime share than for states with more old share. Column 4 provides the response for states whose age share deviates from the national average prime share by one, two, or three percentage points. The blue line represents the volatility over time for states with a national-average age structure for reference. States with higher prime shares display reduced volatility from uncertainty (lying below the blue line), while those with lower shares experience increased volatility (lying above the blue line).

In Row ii, a one percentage point $\Delta SEPU$ shock results in a peak volatility showing up three quarters after the shock for states with a national average age structure (Column 1). Column 2 shows an intensified effect from a one percentage point higher old share, with the total impact from uncertainty shock resulting in a peak value of 190 (Column 3). Column 4 illustrates the dynamic effects of volatility over time, considering states with one, two, and three percentage points higher/lower shares of old. The results indicate that states with higher proportions of old individuals experience a modest increase in uncertainty-driven volatility.

Row iii presents the primary dynamic results of interest, which contrasts the two working-age groups: prime-aged and old-aged. Column 1 illustrates the $\Delta SEPU$ effect for states with national average working-age distributions. In Column 2, states with a one percentage point higher share of prime, in contrast to states with a one percentage point higher share of old relative to the national average, witness a diminished uncertainty impact, with the peak of this effect observed in the fourth quarter post the $\Delta SEPU$ shock.

Given that the average value of cyclical employment volatility stands at 26,921, the average of $\Delta SEPU$ is 9.92, and the coefficient in the fourth quarter post-shock is 170, the uncertainty elasticity of volatility computes to 6.3% (as $\frac{170\times9.92}{26{,}921}$). A one-percentage-point increase in the $\Delta SEPU$ associates with a 6.3% increase in volatility for states with an average age structure, with the effect peaking four quarters post an uncertainty shock. However, this elasticity drops by 4.4% (as $\frac{(120)\times 9.92}{26{,}921}$), which represents a 70% reduction during the fourth quarter (as $\frac{-120}{170}$). Beyond its significance and substantial magnitude, the impact of uncertainty shock is also persistent, with significance with one or two Newey-West robust standard errors remaining up to the eight quarters.

Column 3 considers the one percentage higher share of prime age structure, with the uncertainty impact still positive but smaller and this effect is muted since the fourth quarter. Column 4 shows the estimates for states deviating from the national average age share by one, two, or three percentage points. Specifically, the blue line represents states with the national average age structure for reference. Above it are lines representing states with one, two, and three percentage points lower prime share relative to the national average; these lines reveal a substantial increase in uncertainty-driven volatility. Conversely, the lines below represent states with one, two, and three percentage points greater prime shares compared to those with greater old shares. These states experience a substantial reduction in employment volatility after an economic policy uncertainty shock.

In summary, the demographic effects of prime and old on economic uncertainty differ significantly. Specifically, states with a higher share of prime exhibit diminished employment volatility over eight quarters post the economic policy uncertainty shock, whereas states with a higher share of old exhibit the opposite trend.

6.3 Dynamic Response of Job Gains, Job Losses and Participation

Following the decomposition exploration from the IV regression section, this subsection presents the LP-IV results with dynamic responses to employment volatility following the economic policy uncertainty shock. Two decompositions are conducted: one focusing on the volatility of employment transitions of job gains versus job losses, and the other on the volatility of transitions between employment and unemployment states, versus the volatility in changes in labor force participation. LP-IV results are presented in Figures 7 to 10. Overall, the prime demographic consistently exhibits a negative impact on various labor market volatilities post-economic policy uncertainty over the reported eight quarter horizons. In contrast, the impact from states with a higher old cohort share is muted. These patterns are consistent with the main results from the LP-IV regression on employment volatility.

Figure 7 shows that states with a higher prime share experience reduced job gains volatility following an economic policy uncertainty shock. However, the effect is not significant until four quarters after the shock. Surprisingly, states with a significant older demographic also witness a decrease in this volatility, which is not the case for the previous results on employment volatility. The last row facilitates the comparison of the uncertainty effect between states with a higher share of prime relative to states with a higher share of old. Overall, the comparison shows that states with a higher share of prime (lines below the blue line in the last column) exhibit lower job gains volatility compared to states with a higher share of old (lines above the blue line in the last column). Although the significance and magnitude are relatively smaller compared to the previous findings on employment volatility, the overall effect holds.

Figure 8 focuses on the volatility of job loss. In the first row, states with a higher share of the prime demographic consistently exhibit a reduction in the total uncertainty-impacted volatility of job loss. States containing one, two, and three higher percentage points of prime exhibit lower uncertainty-induced volatility post the shock, with lines representing higher prime share lying below the blue line in the figure to the right. The second row shows that states characterized by the old demographic also display a negative demographic effect; however, the effect is small in magnitude and less significant over time compared to that of prime. This difference is particularly noticeable in the second quarter following the shock. A comparative analysis in the last row demonstrates that states with a higher prime share experience considerably reduced volatility compared to those characterized by the old demographic. With each percentage point increase in the share of prime, states exhibit a lower total uncertainty-impact volatility, as depicted in the figure to the right.

Figure 9 reports the estimates on unemployment volatility over time. States characterized by a rich prime demographic report diminished unemployment volatility, peaking in the fourth quarter after the shock (as shown in the second column in the first row), which is consistent with the previous findings. The uncertainty impact associated with higher share of old demographic is relatively muted (as indicated in the second column of the second row). States with a larger share of prime relative to a larger share of old witness an almost 120-unit reduction in unemployment volatility for each additional percentage share (as displayed in the second column of the last row). These results are consistent with the previous main dynamic results on employment volatility.

Furthermore, Figure 10 demonstrates that states with a higher share of the prime demographic exhibit substantially lower labor-force participation volatility (the second column in the first row). In contrast, this uncertainty impact is nearly insignificant results for the old demographic (second column in the second row). Comparing the effects in the last row from states with one, two, and three percentage points higher share of prime relative to states with one, two, and three percentage points higher share of old, as shown in the second figure to the left, the comparison demonstrates that a higher percentage share of the prime demographic correlates with a 40-unit decline in participation volatility four quarters after the economic uncertainty shock.

When comparing the dynamic uncertainty impact between the response of volatility of job gains and job loss, it becomes evident that the demographic impact on volatility of job loss contributes more than that from the volatility of job gains. Similarly, when comparing the dynamic response on volatility of unemployment and volatility of labor-force participation, the demographic impact on the volatility of unemployment contributes more than that of employment volatility. These results remain consistent with the findings from the IV regression.

7 Conclusion and Discussion

This study investigates the relationship between age structure, labor-market volatility, and economic uncertainty in the United States. The results show that states with a higher proportion of prime individuals (aged 25-54) among working-age (aged 16-64) are less affected by economic uncertainty shocks compared to states with older working-age populations. Using quarterly data from 2000Q1 to 2017Q4, this paper employs instrumental variable regressions and LP-IV to quantify the effect of increased economic uncertainty on employment volatility. Lagged birth rates instrument for the current working-age composition, addressing potential omitted-variable concerns. Similarly, national Economic Policy Uncertainty (EPU) is used as an instrument for state-level $\Delta SEPU$.

The IV estimation results show that for every one-percentage-point increase in the $\Delta SEPU$, there's a 3.2% increase in volatility. However, the volatility increase is reduced by 1.8% for each higher percentage point in prime-aged share, which counts for 55% reduction in economic policy uncertainty effects. Decomposition of this effect suggests that the diminished volatility in job losses and unemployment status accounts for most of the prime-age effect. Robustness checks with varying regression specifications, which include different controls such as state demographics, education, income types, welfare policies, and state political climate, yield results consistent with the main findings.

Local projection-IV (LP-IV) estimates suggest that employment volatility due to uncertainty peaks in the fourth quarter after a shock. For states with a higher proportion of prime-aged workers, this volatility is less pronounced, with a significant 70% reduction in employment volatility induced by economic uncertainty for every additional percentage point of prime-aged workers.

This research sheds light on the impact of age heterogeneity on state labor market volatility in response to various measures of economic uncertainty. As Baby Boomers continue to retire and the composition of the US labor market changes, future research should look into the implications of these demographic trends for policy. Furthermore, additional studies may reveal other ways in which the age distribution influences the labor market.

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Tables

Table 1: Summary of Main Variables

	Mean	Min	Max	SD
Emp. Vol. ($Y_{i,t}$)	26,921	681	318,036	3,542
Emp. Vol. %	100	2.5	1181	13
$\Delta SEPU$ ($U_{i,t}$)	9.92	-92.78	616.47	51.96
ΔEPU (N_t)	1.71	-31.63	46.94	16.61
$\boldsymbol{D_{i,t}}$				
Young (15-24)	21.16	17.77	30.48	1.52
Prime (25-54)	61.37	54.96	68.26	2.41
Old (55-64)	17.47	9.84	24.68	2.65
$\boldsymbol{B_{i,t}}$				
BirthRate (15-24)	15.29	11.00	26.70	1.82
BirthRate (25-54)	19.22	14.32	28.74	2.49
BirthRate (55-64)	25.02	16.24	35.65	3.41

Note: This is a summary of the main variables on a state-quarterly basis from 2000Q1 to 2017Q4. Alaska and Hawaii are excluded due to missing birth rates data before 1956. The three working age range (15-64) shares add up to 100%. Birth rates for each age group are calculated using a rolling window based on corresponding lagged years of birth rates. Cyclical employment volatility is calculated as the standard deviation of cyclical employment with a centered 17-quarter rolling window. With 112 missing values in $\Delta SEPU$, the total observations in this sample amount to 3,416.

Table 2: First Stage

	(1) $B_{i,t-k}$ Young	(2) $B_{i,t-k}$ Prime	(3) $B_{i,t-k}$ Old	(4) N_t Young	(5) N_t Prime	(6) N_t Old	(7) $N_t * B_{i,t-k}$ Young	(8) $N_t * B_{i,t-k}$ Prime	(9) $N_t * B_{i,t-k}$ Old
$Coef.$	0.645***	1.028***	0.945***	1.519***	1.517***	1.503***	94889***	-111752***	-26737***
	(0.0191)	(0.0161)	(0.0270)	(0.0515)	(0.0509)	(0.0519)	(26818)	(29604)	(5691)
$F-stat$	823.2	341.6	74.41	18.65	19.01	19.33	21.22	16.41	17.49
$Obs.$	3416	3416	3416	3416	3416	3416	3416	3416	3416

Note: This table presents the 1st stage regression results for three working ages (Equation 3), $\Delta SEPU$ (Equation 4) , and three age interactions (following Equation 5) across US states from 2000Q1 to 2017Q4. Regression incorporates state fixed effects and report Newey-West standard errors. Coefficients are all statistically significant with substantial F-statistic values, suggesting birth rates and national ΔEPU are valid IVs.

Table 3: Main Estimation

	(1) Prime	(2) Old	(3) Prime-Old Baseline
$U_{i,t}$	75.07***	89.45***	86.94***
	(17.88)	(16.44)	(21.90)
$U_{i,t} * Prime_{i,t}$	-28.54**		-48.38**
	(11.93)		(21.18)
$U_{i,t} * Old_{i,t}$		24.62**	
		(12.06)	
$U_{i,t} * Young_{i,t}$			✓
$Young_{i,t}$			✓
$Prime_{i,t}$	✓		✓
$Old_{i,t}$		✓	
$F-stat.$	55.42	73.67	49.19
$Obs.$	3416	3416	3416

Note: This table presents regressions using quarterly data from 2000Q1 to 2017Q4 across states. The dependent variable is cyclical employment volatility. Columns 1-3 provide estimates from the second stage following Equation 6, using birth rates and national ΔEPU as IVs. The regressions are executed for prime, with the results reported in Column 1, old in Column 2, and encompassing both prime and young (with young as a control) in Column 3; hence, it enables a comparison between prime and old. For convenience, the interaction term in Equation 6, represented as $(D_{i,t} - \overline{D}) \times (U_{i,t} - \overline{U})$, is abbreviated as $U_{i,t} \times Prime_{i,t}$ or $U_{i,t} \times Old_{i,t}$. The checked coefficients are not the main interpretation of interest, and thus, they are not reported. The detailed results are available upon request. All regressions include state fixed effects and apply Newey-West standard errors.

Table 4: Reduced Form For Robustness

	(1) Prime Partial	(2) Old Partial	(3) Prime-Old Partial	(4) Prime Reduced	(5) Old Reduced	(6) Prime-Old Reduced
N_t	101.7***	122.1***	113.3***	399.2***	-19.87	144.0
	(23.41)	(21.89)	(26.28)	(142.3)	(98.23)	(173.6)
$N_t * Prime_{i,t}$	-40.14**		-75.46**			
	(17.15)		(34.11)			
$N_t * Old_{i,t}$		26.77				
		(19.02)				
$N_t * Prime\,Birth_{i,t}$				-15.62**		-42.80***
				(6.772)		(16.47)
$N_t * Old\,Birth_{i,t}$					5.293	
					(3.737)	
$N_t * Young_{i,t}$			✓			✓
$Young_{i,t}$			✓			✓
$Prime_{i,t}$	✓		✓	✓		✓
$Old_{i,t}$		✓			✓	
$F-stat.$	68.12	90.73	61.23	78.37	110.9	70.80
$Obs.$	3416	3416	3416	3416	3416	3416

Note: This table presents partially and fully reduced-form regressions using quarterly data from 2000Q1 to 2017Q4 across states. The dependent variable is cyclical employment volatility. Columns 1-3 provide estimates with ΔEPU as an independent variable directly, while Columns 4-6 execute regressions following Equation 6, incorporating ΔEPU and lagged birth rates as independent variables. All regressions include state fixed effects and apply Newey-West standard errors.

Table 5: Analyzing for Volatility of Job Gains and Loss

	(1) $Gains$ Prime	(2) $Gains$ Old	(3) $Gains$ Prime-Old	(4) $Loss$ Prime	(5) $Loss$ Old	(6) $Loss$ Prime-Old
$U_{i,t}$	21.05***	18.85***	23.84***	18.65***	19.64***	21.63***
	(3.366)	(3.398)	(4.730)	(4.613)	(4.494)	(5.918)
$U_{i,t} * Prime_{i,t}$	-1.193		-9.718**	-8.043**		-15.48***
	(2.371)		(4.766)	(3.204)		(5.760)
$U_{i,t} * Old_{i,t}$		-3.726			3.901	
		(4.367)			(4.573)	
$U_{i,t} * Young_{i,t}$			✓			✓
$Young_{i,t}$			✓			✓
$Prime_{i,t}$	✓		✓	✓		✓
$Old_{i,t}$		✓			✓	
$F-stat.$	98.94	109.2	77.02	61.71	75.20	53.15
$Obs.$	3416	3416	3416	3416	3416	3416

Note: This table reports regressions results following Equation 6 using quarterly data from 2000Q1 to 2017Q4 across states. The dependent variable for the first three columns is job gains volatility, and for the next three columns, it is job loss volatility. Column 1 is regressed on prime, Column 2 is on old, and Column 3 on both prime and young, treating old as the omitted reference group. All regressions employ birth rates and national ΔEPU as IVs for working age share and $\Delta SEPU$, respectively. All models incorporate state fixed effects and utilize Newey-West standard errors.

Table 6: Analyzing for Volatility of Unemployment and Participation

	(1) $Unemp$ Prime	(2) $Unemp$ Old	(3) $Unemp$ Prime-Old	(4) $Participate$ Prime	(5) $Participate$ Old	(6) $Participate$ Prime-Old
$U_{i,t}$	71.97***	86.27***	84.18***	12.09	10.71*	14.98*
	(14.66)	(14.53)	(20.62)	(7.433)	(6.471)	(8.103)
$U_{i,t} * Prime_{i,t}$	-22.15**		-41.80*	-7.116		-13.19*
	(8.685)		(21.56)	(6.003)		(7.687)
$U_{i,t} * Old_{i,t}$		16.56			4.234	
		(10.92)			(5.832)	
$U_{i,t} * Young_{i,t}$			✓			✓
$Young_{i,t}$			✓			✓
$Prime_{i,t}$	✓		✓	✓		✓
$Old_{i,t}$		✓			✓	
$F-stat.$	52.36	52.46	44.64	148.3	159.4	122.0
$Obs.$	3416	3416	3416	3416	3416	3416

Note: This table reports regressions results following Equation 6 using quarterly data from 2000Q1 to 2017Q4 across states. The dependent variable for the first three columns are unemployment volatility and labor-force participation volatility for the last three columns. Column 4 is regressed on prime, Column 2 on old, and Column 3 on both prime and young, treating old as the omitted reference group. All regressions employ birth rates and national ΔEPU as IVs for working age share and $\Delta SEPU$, respectively. All models incorporate state fixed effects and utilize Newey-West standard errors.

Table 7: Regression with Demographics

	(1) baseline	(2) $femar$	(3) $fework$	(4) $white$	(5) $black$	(6) $immigrant$	(7) $hisp$	(8) $hrwork$	(9) $lwskill$
$U_{i,t}$	84.93***	84.99***	79.87***	87.77***	83.79***	74.43***	83.09***	91.67***	90.48***
	(21.09)	(20.52)	(20.50)	(22.02)	(20.81)	(16.68)	(19.29)	(22.80)	(21.83)
$U_{i,t} * Prime$	-48.38**	-43.93**	-48.78**	-46.55**	-52.38**	-15.76*	-28.16**	-64.83**	-55.00**
	(21.18)	(17.92)	(20.95)	(20.28)	(22.57)	(8.321)	(12.96)	(26.95)	(24.30)
$U_{i,t} * Young_{i,t}$	✓	✓	✓	✓	✓	✓	✓	✓	✓
$Young_{i,t}$	✓	✓	✓	✓	✓	✓	✓	✓	✓
$Prime_{i,t}$	✓	✓	✓	✓	✓	✓	✓	✓	✓
$F - stat.$	49.19	49.16	48.21	49.28	47.51	58.98	55.70	43.59	47.75
$Obs.$	3416	3416	3416	3416	3416	3416	3416	3416	3416

Note: This table presents the results of the baseline regression with various demographic variables in accordance with Equation 20. Rows 1 and 2 report the regression results for $U_{i,t}$ and $U_{i,t} * Prime$, which are the primary regressions of interest. Subsequent rows provide estimates for the interaction terms of $U_{i,t}$ with different demographic controls. The dependent variable is cyclical employment volatility. All regressions utilize ΔEPU and lagged birth rates as instruments, include state fixed effects, and apply Newey-West standard errors.

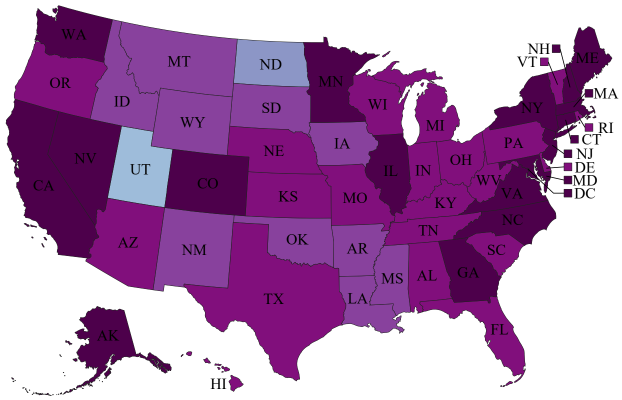
Table 8: Regression with State Income

	(1) baseline	(2) $perinc$	(3) $wage$	(4) $constrcut$	(5) $manufact$	(6) $retailtrade$	(7) $transport$	(8) $health$
$U_{i,t}$	84.93***	74.83***	75.34***	73.87***	72.63***	64.72***	73.74***	71.08***
	(21.09)	(13.59)	(13.90)	(15.61)	(15.66)	(14.07)	(14.26)	(13.56)
$U_{i,t} * Prime$	-48.38**	-17.99**	-22.12**	-27.00**	-39.26***	-29.68***	-23.15**	-14.38*
	(21.18)	(8.994)	(9.173)	(11.24)	(14.45)	(10.32)	(10.96)	(8.672)
$U_{i,t} * Young_{i,t}$	✓	✓	✓	✓	✓	✓	✓	✓
$Young_{i,t}$	✓	✓	✓	✓	✓	✓	✓	✓
$Prime_{i,t}$	✓	✓	✓	✓	✓	✓	✓	✓
$F - stat.$	49.19	54.26	57.44	59.61	53.33	60.27	61.61	52.31
$Obs.$	3416	3416	3416	3400	3404	3416	3400	3416

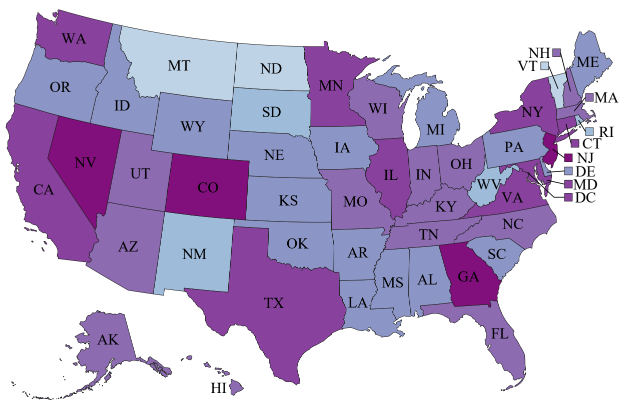
Note: This table presents the results of the baseline regression with different state sectoral income variables. *Note:* This table presents the results of the baseline regression with various demographic variables in accordance with Equation 20. Rows 1 and 2 report the regression results for $U_{i,t}$ and $U_{i,t} * Prime$, which are the primary regressions of interest. Subsequent rows provide estimates for the interaction terms of $U_{i,t}$ with different state personal income, wage and salary, and various sectoral income controls. The dependent variable is cyclical employment volatility. All regressions utilize ΔEPU and lagged birth rates as instruments, include state fixed effects, and apply Newey-West standard errors.

Figures

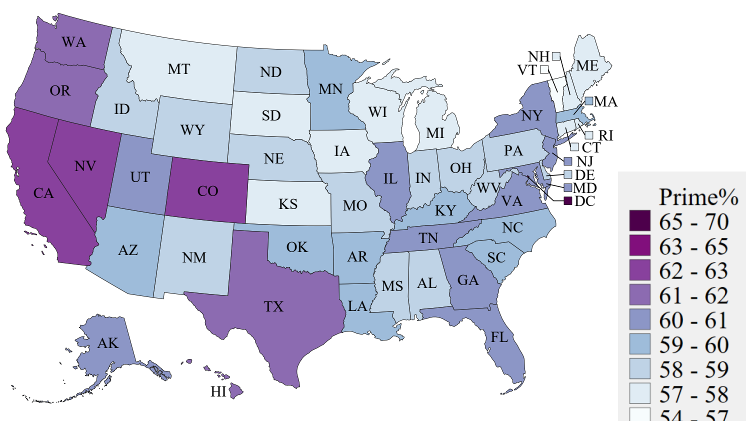
Figure 1: Evolution of prime Age Share



(a) 2001Q4



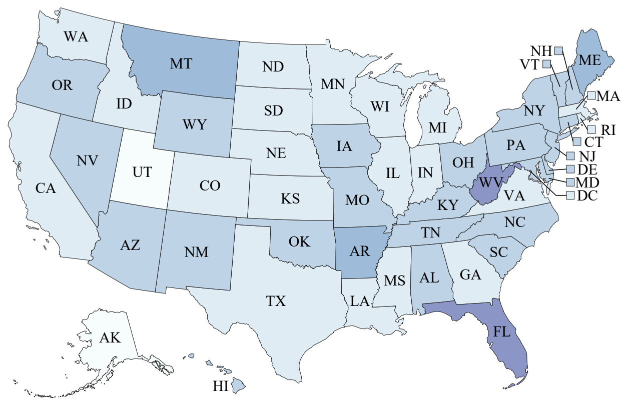
(b) 2008Q4



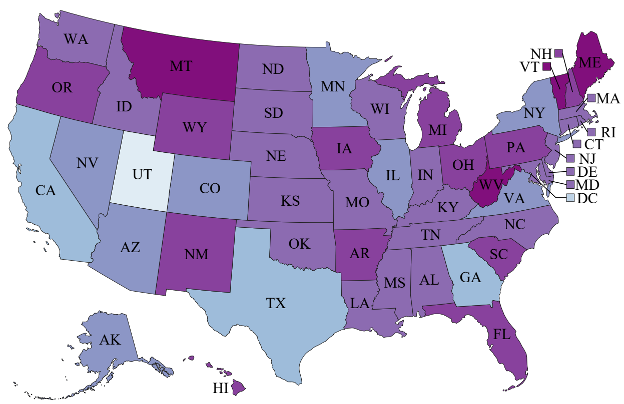
(c) 2017Q4

Note: The figures above show the share of prime-aged individuals (those aged 25-54 out of the 15-64) across states for 2001Q1, 2008q4, and 2017Q4. Over the time period from 2001Q4 to 2017Q4, there has been a noticeable decreasing trend.

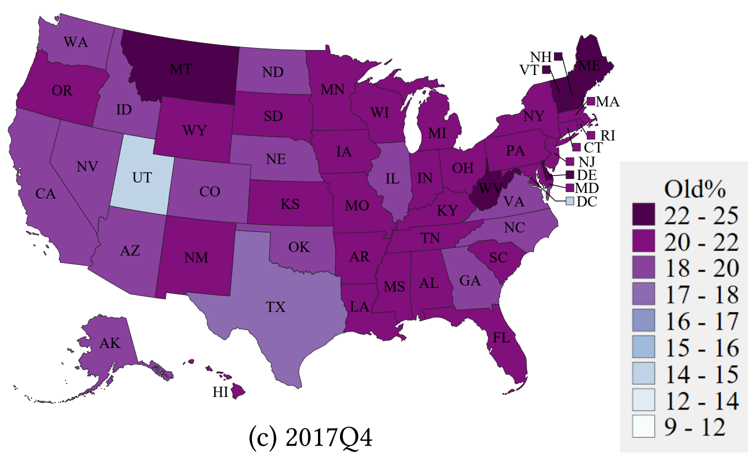
Figure 2: Evolution of old Age Share



(a) 2001Q4



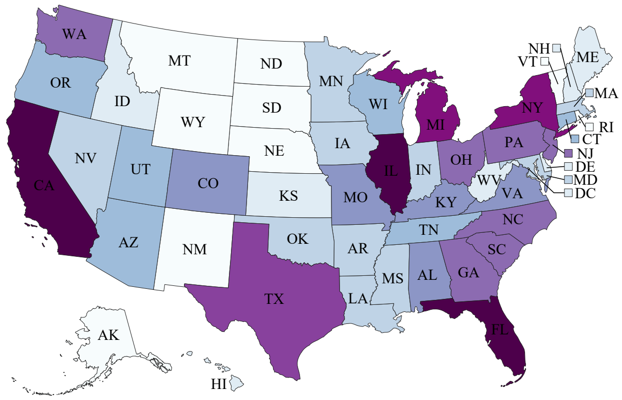
(b) 2008Q4



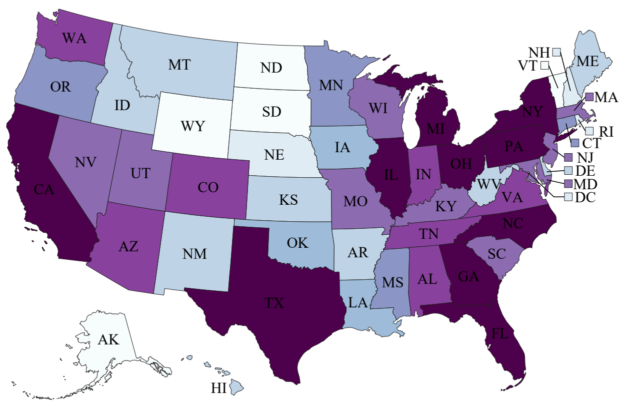
(c) 2017Q4

Note: The figures above show the share of old-aged individuals (those aged 55-64 out of the 15-64) across states for 2001Q4, 2008q4, and 2017Q4. Over the time period from 2000 to 2017, there has been a noticeable increasing trend.

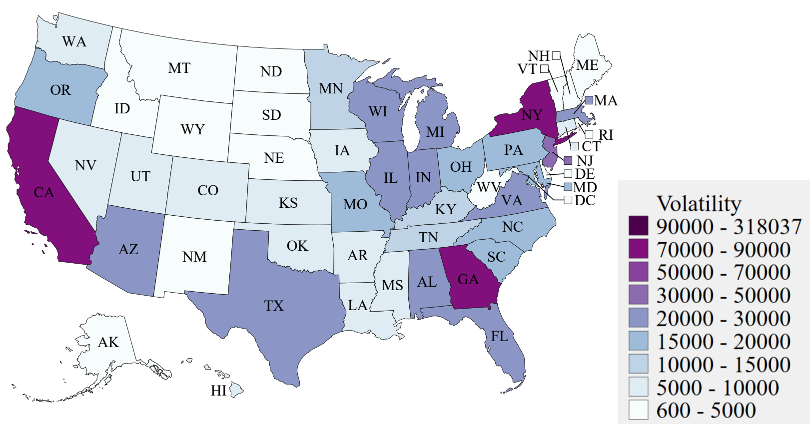
Figure 3: Evolution of Cyclical Employment Volatility



(a) 2001Q4



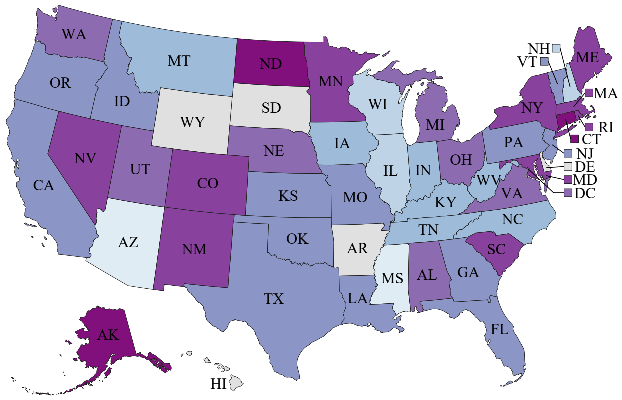
(b) 2008Q4



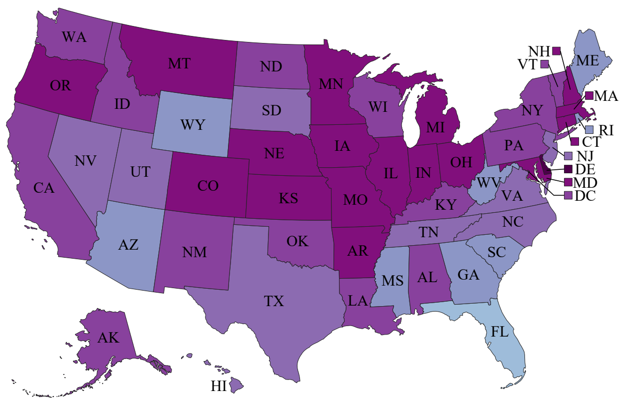
(c) 2017Q4

Note: The figures provided display the cyclical employment volatility (definition provided in the main context) across states for 2001Q4, 2008Q4, and 2017Q4. Overall, the level of employment volatility is highest during the Great Recession in 2008Q4, followed by the 2001 Recession, with a significantly lower level of volatility during the economic boom of 2017Q4. Larger states such as California and Texas typically exhibit higher volatility, while mid-west states like South Dakota and Wyoming demonstrate lower volatility during the specified periods.

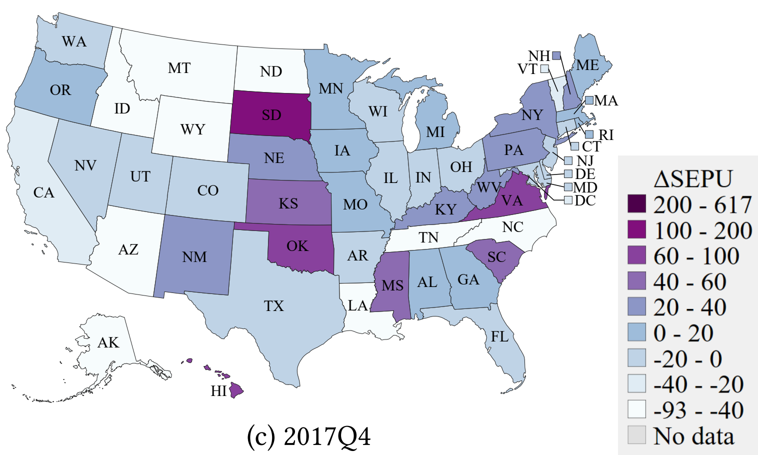
Figure 4: Evolution of State Economic Policy Uncertainty



(a) 2001Q4



(b) 2008Q4

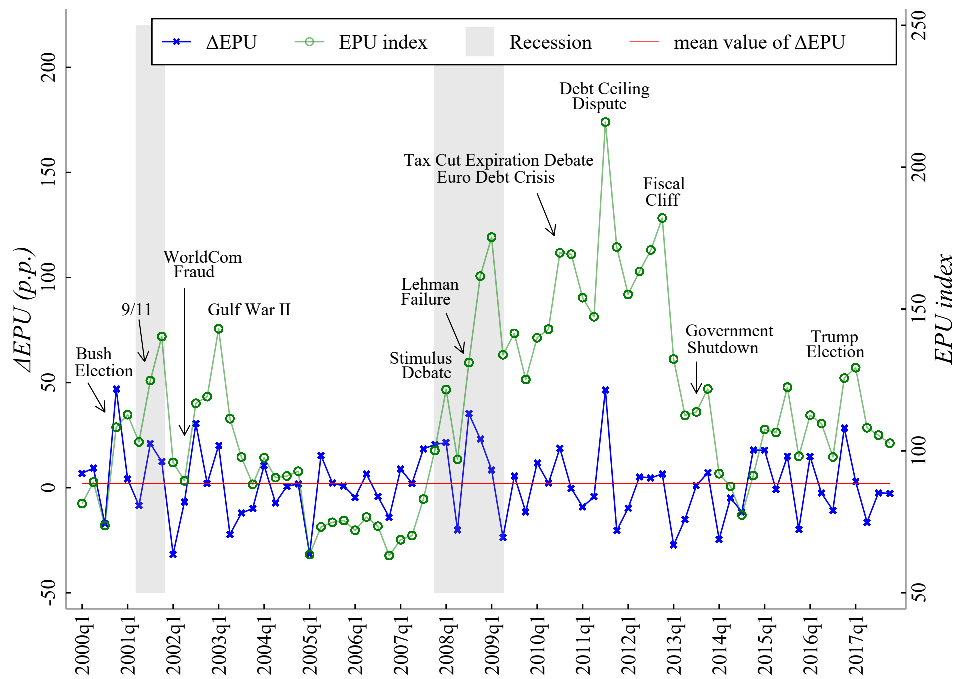


(c) 2017Q4

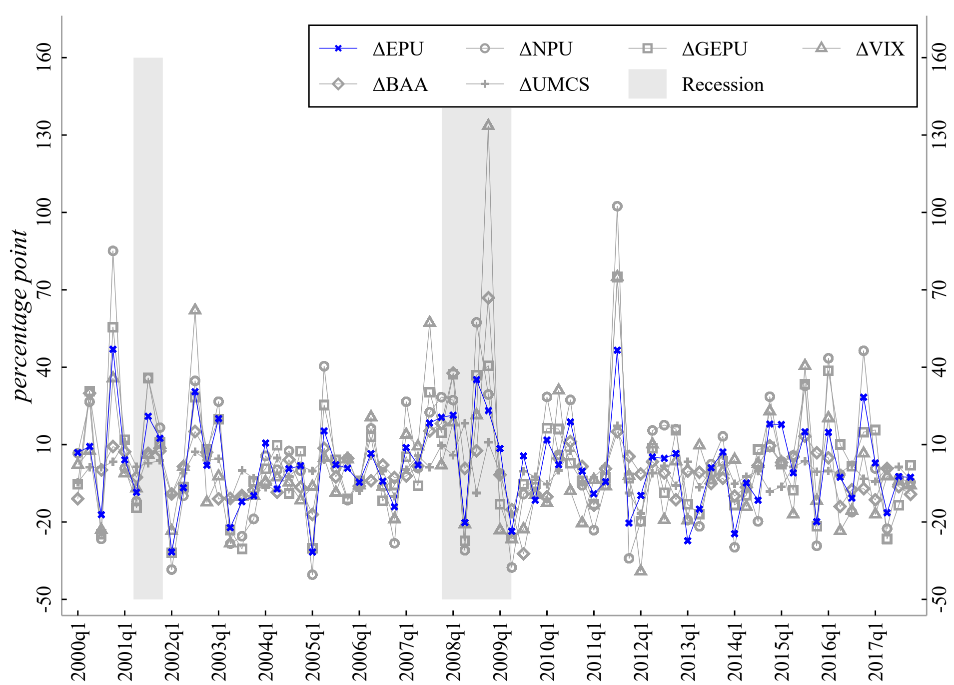
Note: The figures represents the state economic policy uncertainty ($\Delta SEPU$) measures for 2001Q4, 2008Q4, and 2017Q4. This variable is calculated as the percentage change in the state EPU index from Baker, Davis, and Levy (2022). During the Great Recession, the measure for 2008Q4 exhibits greater uncertainty than the other quarters. Specifically, states like Alaska and North Dakota, which are reliant on crude oil exports, experienced high uncertainty in both 2001 and 2008, with these uncertainty levels significantly decreased during the economic boom of 2017Q4.

Figure 5: Visualizing Economic Uncertainty Measures

(a) Economic Policy Uncertainty

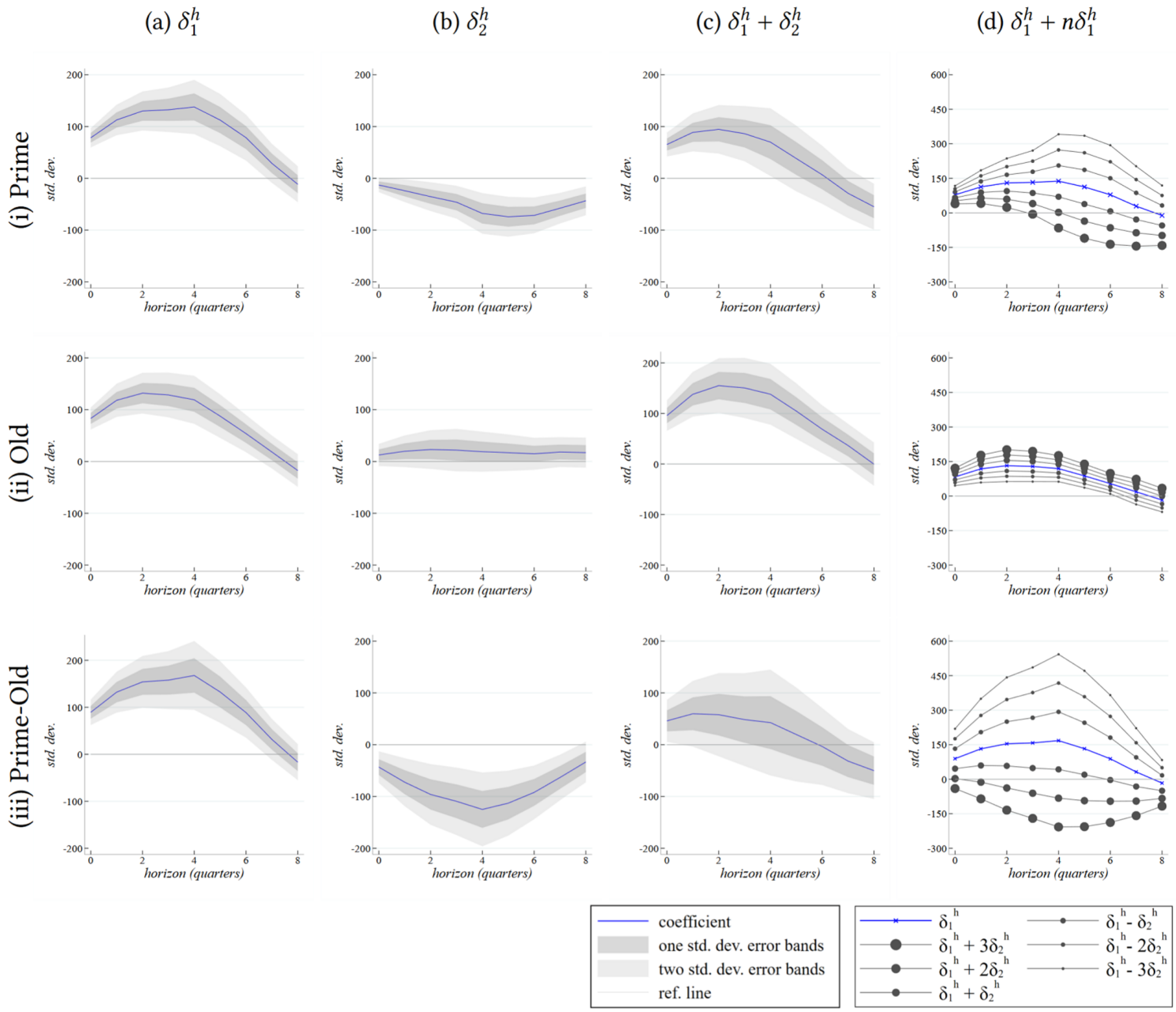


(b) Other Measures



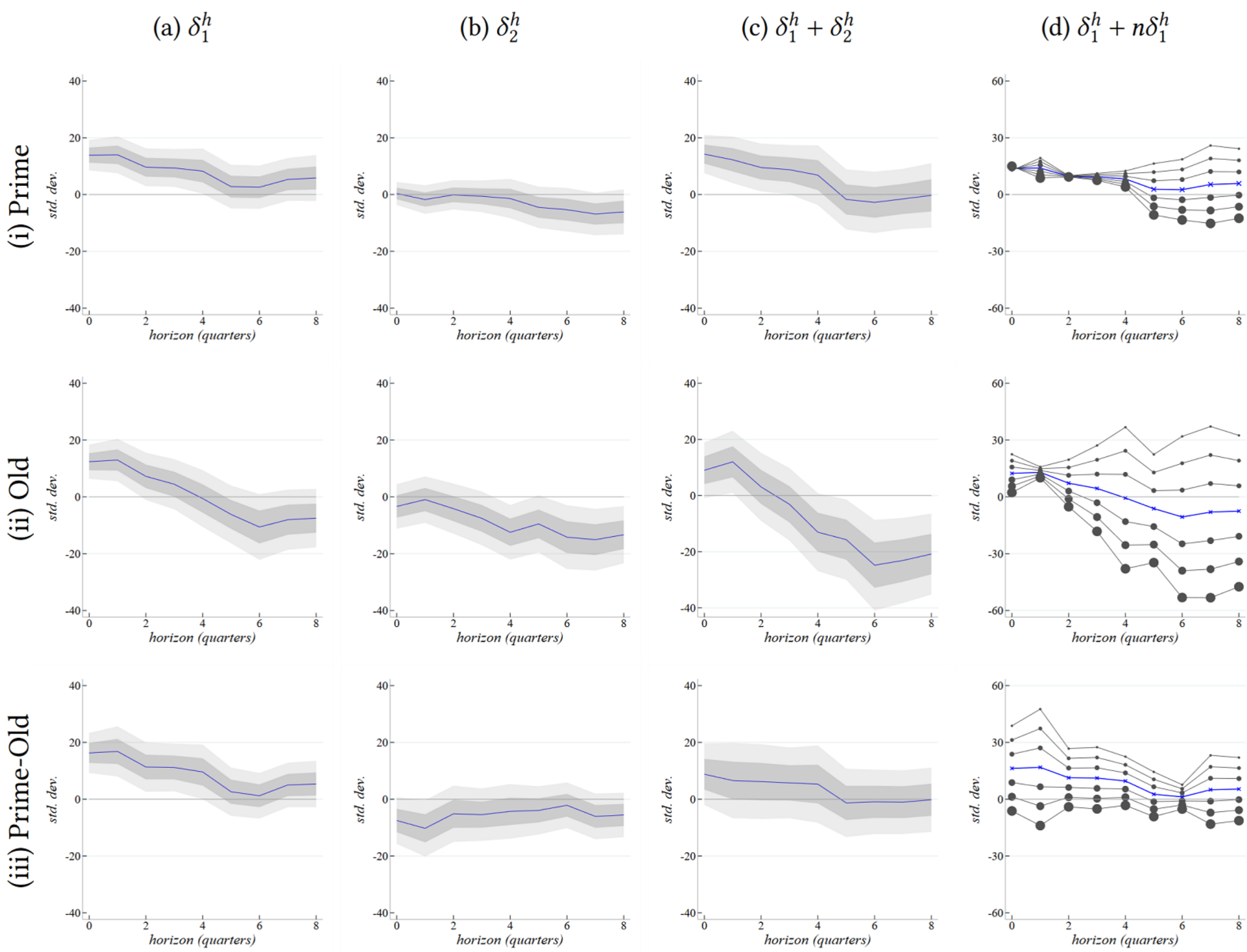
Note: EPU index in Panel A (illustrated in green) is proposed by Baker, Bloom, and Davis (2016), and the data are collected from the policy uncertainty website. The blue curve depicts the percentage changes of the index, referred to as ΔEPU in this paper. Panel B depicts five other national uncertainty measures along with ΔEPU, all in percentage changes.

Figure 6: Impulse Response: Employment Volatility to Economic Policy Uncertainty and Age Distribution



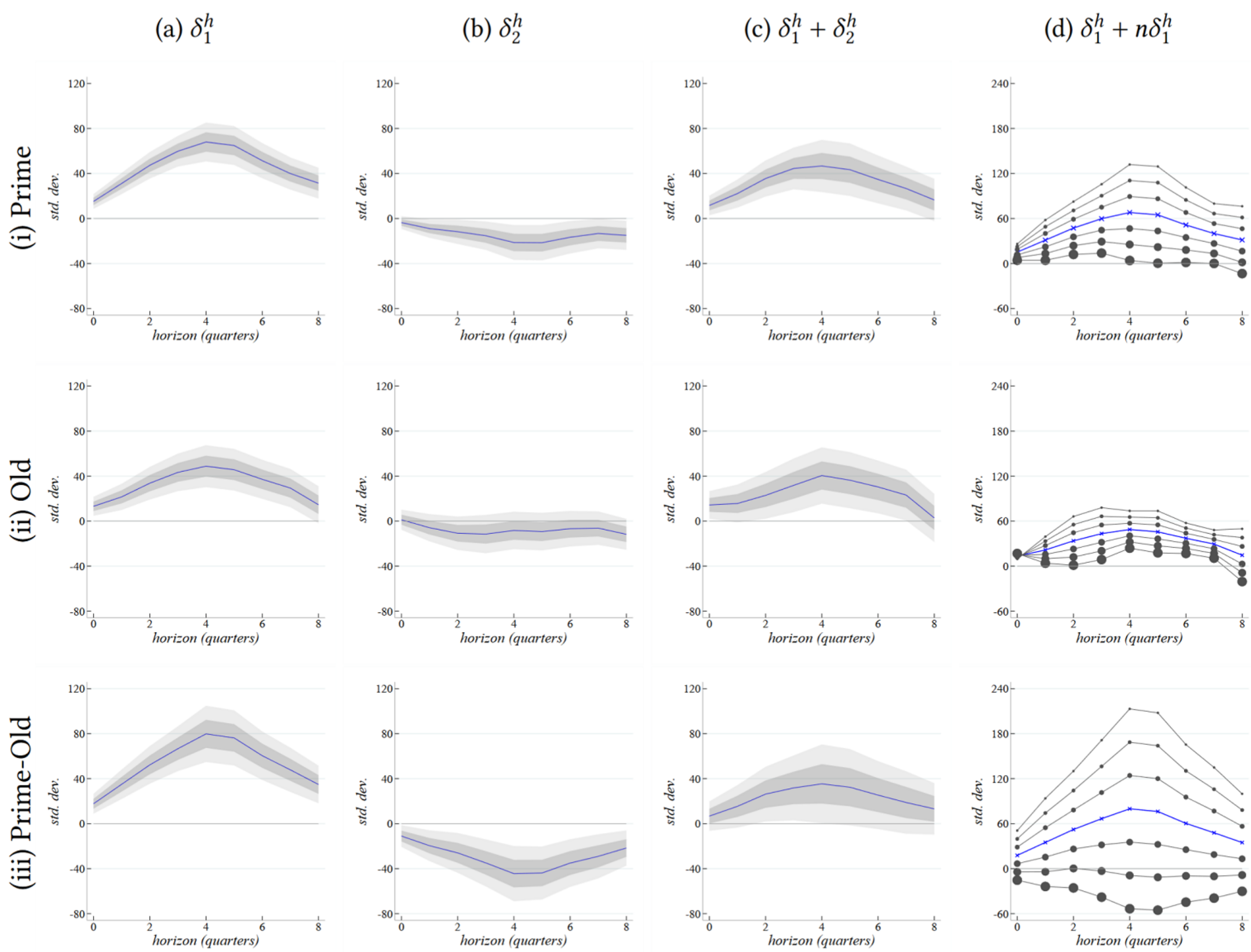
Note: The figures display the LP-IV Impulse Response Function (IRF) of cumulative cyclical employment volatility in response to various uncertainty measures among ages groups, as described by Equation 10. These figures elucidate the dynamic shifts in employment volatility due to a one percentage point increase in the state economic policy uncertainty among prime, old, and the comparison between them. Row 1 presents the estimates for the LP regression on prime. Row 2 showcases the regression results for old. The final row contrasts the two by considering old as the reference group. Column 1 presents estimates for the coefficient δ_1^h, Column 2 for δ_2^h, and Column 3 for $\delta_1^h + \delta_2^h$, which represents the primary coefficient of interest. Meanwhile, Column 4 reports estimates on $\delta_1^h + n \cdot \delta_2^h$, where n ranges from -3 to 3, corresponding to a one, two, or three percentage point deviation (lower/higher) in the share of working age (prime or old) relative to the national average, as depicted in the figures. The vertical axes illustrate changes in standard deviations of employment volatility from the baseline. The grey areas indicate one and two Newey-West standard deviation confidence intervals for each coefficient estimate. For more details, refer to the main content of the paper.

Figure 7: Impulse Response: Job Gains Volatility to Economic Policy Uncertainty and Age Distribution



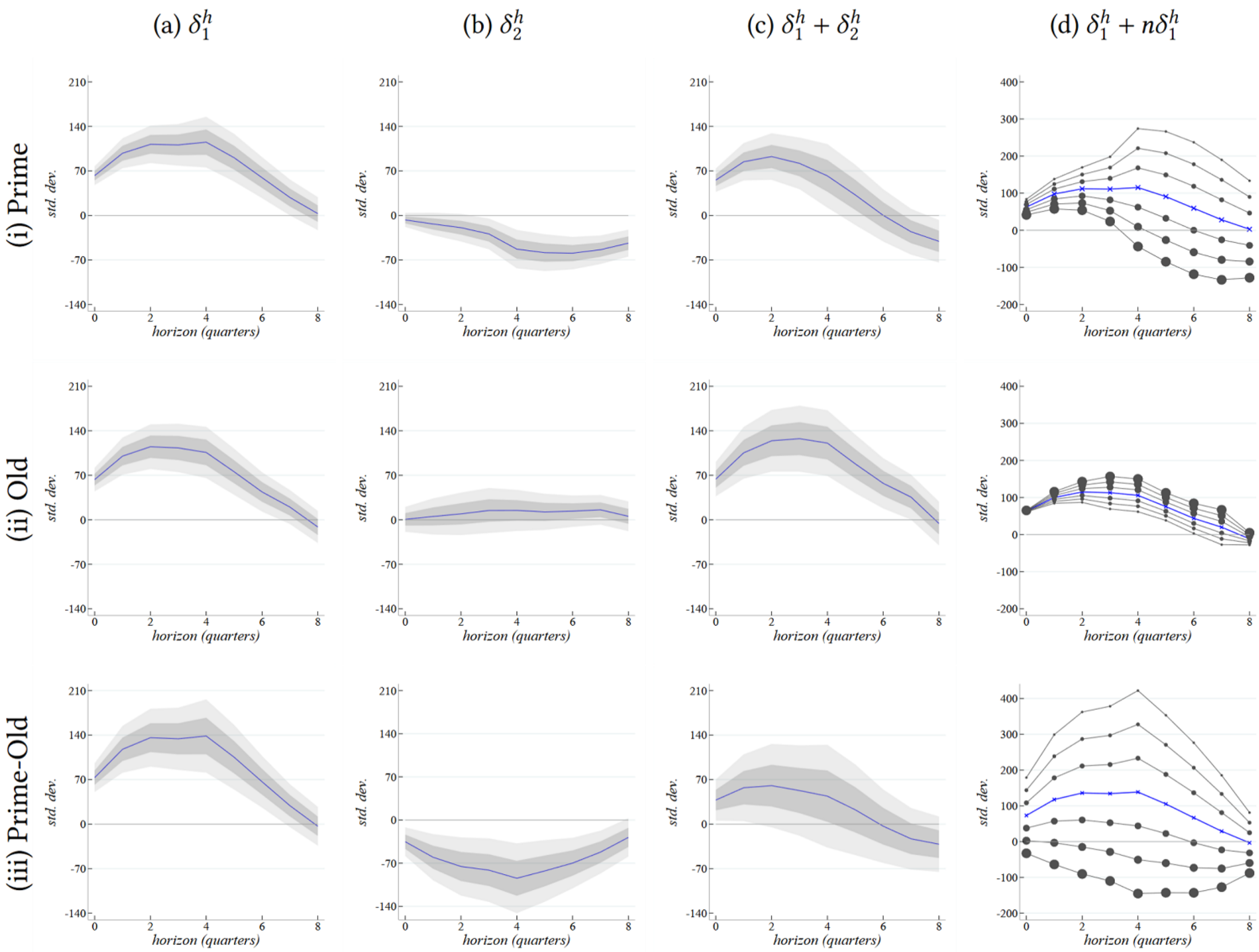
Note: The figures display the LP IRF of cumulative job gains volatility in response to various uncertainty measures and among age groups, as described by Equation 10, with the outcome variable switching to job gains volatility. These figures illustrate the dynamic responses in volatility due to a one percentage point increase in the state economic policy uncertainty among prime, old, and the comparison between them. Rows present the estimates for LP regression on prime, old, and the comparison with old as the base separately. Columns presents estimates for the coefficient δ_1^h, δ_2^h, $\delta_1^h + \delta_2^h$, and $\delta_1^h + n \cdot \delta_2^h$ respectively. The vertical axes illustrate changes in standard deviations of volatility. The grey areas indicate one and two Newey-West standard deviation confidence bands for each coefficient estimate. For more details, For more details, refer to the main content of the paper.

Figure 8: Impulse Response: Job Loss Volatility to Economic Policy Uncertainty and Age Distribution



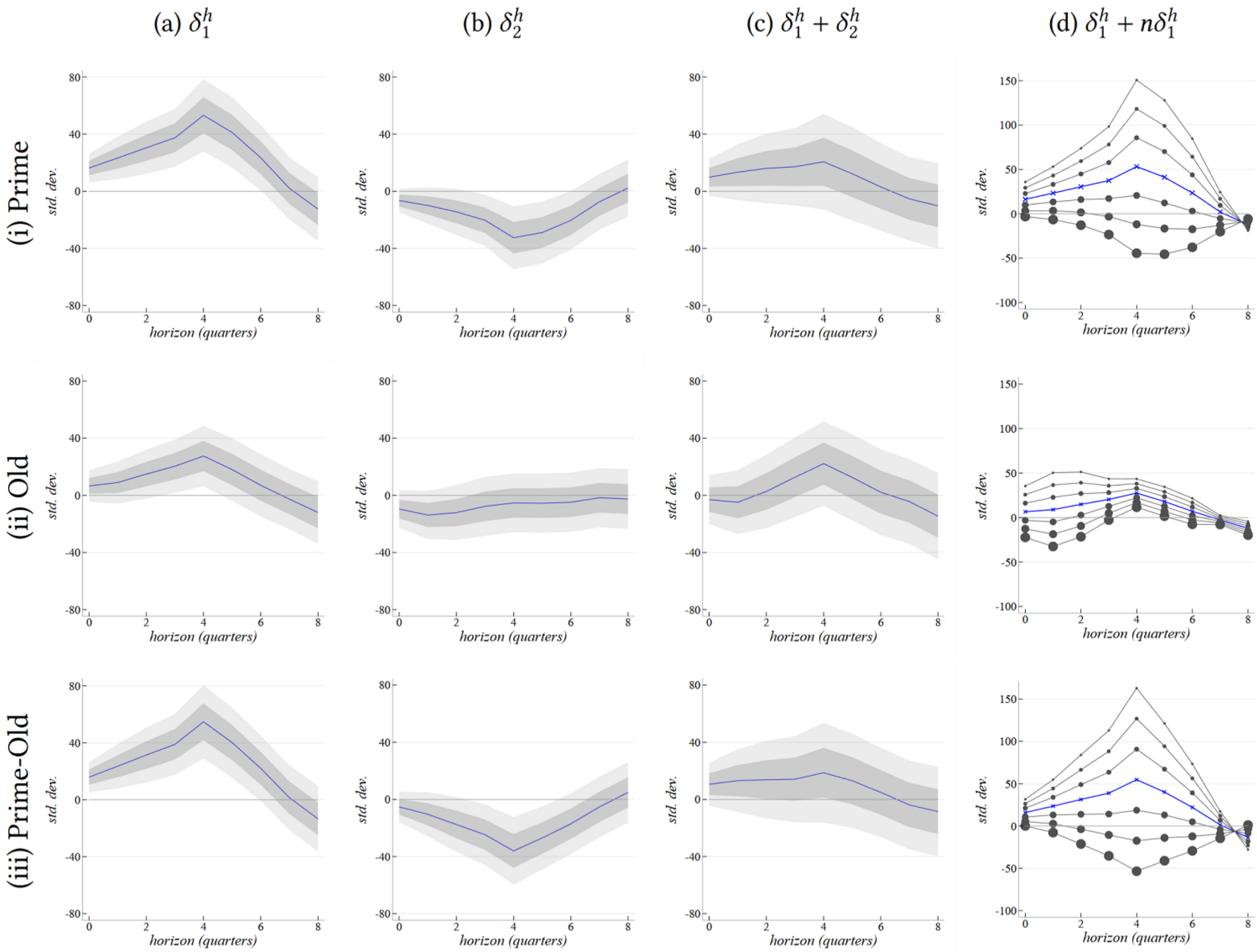
Note: The figures display the LP IRF of cumulative job loss volatility in response to various uncertainty measures and among age groups, as described by Equation 10, with the outcome variable switching to job loss volatility. These figures illustrate the dynamic responses in volatility due to a one percentage point increase in the state economic policy uncertainty among prime, old, and the comparison between them. Rows present the estimates for LP regression on prime, old, and the comparison with old as the base separately. Columns presents estimates for the coefficient δ_1^h, δ_2^h, $\delta_1^h + \delta_2^h$, and $\delta_1^h + n \cdot \delta_2^h$ respectively. The vertical axes illustrate changes in standard deviations of volatility. The grey areas indicate one and two Newey-West standard deviation confidence bands for each coefficient estimate. For more details, For more details, refer to the main content of the paper.

Figure 9: Impulse Response: Unemployment Volatility to Economic Policy Uncertainty and Age Distribution



Note: The figures display the LP IRF of cumulative unemployment volatility in response to various uncertainty measures and among age groups, as described by Equation 10, with the outcome variable switching to unemployment volatility. These figures illustrate the dynamic responses in volatility due to a one percentage point increase in the state economic policy uncertainty among prime, old, and the comparison between them. Rows present the estimates for LP regression on prime, old, and the comparison with old as the base separately. Columns presents estimates for the coefficient δ_1^h, δ_2^h, $\delta_1^h + \delta_2^h$, and $\delta_1^h + n \cdot \delta_2^h$ respectively. The vertical axes illustrate changes in standard deviations of volatility. The grey areas indicate one and two Newey-West standard deviation confidence bands for each coefficient estimate. For more details, For more details, refer to the main content of the paper.

Figure 10: Impulse Response: Labor-Force Participation Volatility to Economic Policy Uncertainty and Age Distribution



Note: The figures display the LP IRF of cumulative labor-force participation volatility in response to various uncertainty measures and among age groups, as described by Equation 10, with the outcome variable switching to participation volatility. These figures illustrate the dynamic responses in volatility due to a one percentage point increase in the state economic policy uncertainty among prime, old, and the comparison between them. Rows present the estimates for LP regression on prime, old, and the comparison with old as the base separately. Columns presents estimates for the coefficient δ_1^h, δ_2^h, $\delta_1^h + \delta_2^h$, and $\delta_1^h + n \cdot \delta_2^h$ respectively. The vertical axes illustrate changes in standard deviations of volatility. The grey areas indicate one and two Newey-West standard deviation confidence bands for each coefficient estimate. For more details, For more details, refer to the main content of the paper.

Appendix

A Appendix Tables

Table A.1: Covariance Among Uncertainty Measures

	(1) $\Delta SEPU$	(2) ΔEPU	(3) $\Delta GEPU$	(4) ΔNPU	(5) ΔVIX	(6) ΔBAA	(7) $UMCS$
$\Delta SEPU$	1.000						
ΔEPU	0.456*	1.000					
$\Delta GEPU$	0.427*	0.823*	1.000				
ΔNPU	0.454*	0.946*	0.867*	1.000			
ΔVIX	0.320*	0.602*	0.644*	0.600*	1.000		
ΔBAA	0.287*	0.444*	0.533*	0.434*	0.624*	1.000	
$\Delta UMCS$	0.254*	0.380*	0.384*	0.403*	0.380*	0.432*	1.000

Note: This table displays the correlations among the uncertainty measures used in this paper, with significance levels indicated.

Table A.2: Correlation Among Ages and Age*$\Delta SEPU$ Interactions

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta SEPU * Young$	1.000					
$\Delta SEPU * Prime$	-0.175*	1.000				
$\Delta SEPU * Old$	-0.447*	-0.802*	1.000			
young	-0.003	-0.002	0.003	1.000		
prime	-0.003	-0.001	0.002	0.998*	1.000	
old	0.001	0.000	0.000	0.971*	0.973*	1.000

Note: This table presents correlations among demographic groups and their interactions with $\Delta SEPU$.

Table A.3: Covariance of Birth Rates for Ages 20-29: 2000-2015

	From Basso and Rachedi (2021)	Collected by the author
From Basso and Rachedi (2021)	1.000	
Collected by author	0.996*	1.000

Note: This table displays correlations between birth rates for ages 20-29 from 2000 to 2015 in data collected by the author and data collected by Basso and Rachedi (2021).

Table A.4: Summary Statistics of Supplementary Variables

	Mean	Min	Max	SD	N
Outcome variables					
$Emplevel$	3,000,000	280,000	18,000,000	3,100,000	3416
$CyclicalEmp$	-331	-420,852	381,766	50,319	3416
$Empchange$	5,242	-238,105	294,941	22,908	3416
$CyclicalEmpchange$	-248	-209,477	263,345	17,532	3416
$Gainsvol$	9,067	529	87,886	10,455	3416
$LossVol$	10,058	544	110,075	12,359	3416
$Cyclicalunempvol$	21,190	225	329,513	30,224	3416
$Cyclicalparticipvol$	17,327	706	128,696	18,168	3416
$Cyclicalgainsvol$	7.674	485	64,585	8,413	3416
$Cyclicallossvol$	8,711	529	80,499	10,305	3416
$Cyclicalempchgvol$	11,136	453	91,547	12,680	3416
Uncertainties					
ΔEPU	1.71	-31.63	46.94	16.61	3416
$\Delta GEPU$	3.14	-31.90	74.99	20.87	3416
ΔNPU	3.99	-40.43	102.41	27.18	3416
ΔVIX	1.47	-39.20	133.48	25.84	3416
ΔBAA	0.61	-32.34	66.91	13.20	3416
$UMCS$	-0.15	-16.98	18.24	6.41	3416
$Y_{i,t}$ **with other windows**					
$center-17-quarter$	26,921	681	320,000	35,420	3416
$center-13-quarter$	23,628	452	325,091	32,001	3416
$center-9-quarter$	18,975	240	326,747	26,779	3416
$center-5-quarter$	12,753	54	258,803	19,076	3416
$backward-17-quarter$	26,821	586	318,036	35,486	3416
$forward-17-quarter$	27,426	762	318,036	36,201	3024

Note: This table summarizes supplementary variables used in the paper that were not included in the previous main summary statistics. The sample ranges from 2000Q1 to 2017Q4 for forty-eight states including DC.

Table A.5: Additional Analysis: Volatility of Cyclical Employment and Job Gains/Losses

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Δvol	Δvol	Δvol	vol	vol	vol	vol	vol	vol
	Δemp	Δemp	Δemp	Gains	Gains	Gains	Loss	Loss	Loss
	Prime	Old	Prime -Old	Prime	Old	Prime -Old	Prime	Old	Prime -Old
$U_{i,t}$	32.49***	36.31***	37.01***	11.22***	11.19***	13.55***	18.78***	18.37***	21.85***
	(5.494)	(5.420)	(6.914)	(2.296)	(2.487)	(3.292)	(3.646)	(3.835)	(4.907)
$U_{i,t} * Prime$	-9.109**		-17.54***	-2.274		-8.970***	-4.689*		-12.54***
	(4.060)		(6.786)	(1.794)		(3.375)	(2.769)		(4.716)
$U_{i,t} * Old$		8.703**			-0.0736			-1.482	
		(4.428)			(2.451)			(3.798)	
$Obs.$	3416	3416	3416	3416	3416	3416	3416	3416	3416
$F-stat.$	89.82	89.79	63.41	151.3	194.7	109.1	72.36	88.35	57.83

Note: This table displays the regression results for employment volatility decomposition. Columns 1-3 present results for the volatility of cyclical employment changes, Columns 4-6 for volatility of cyclical job gains, and Columns 7-9 for volatility of cyclical job losses. The results are consistent with those reported in the main text.

B Uncertainty Index Data Description

This section provides more detailed information about the uncertainty measures, their characteristics, construction, and sources. Note that the indices below are all taken as percentage changes and multiplied by 100%, which yields the uncertainty measures used in this paper.

EPU - US economic policy uncertainty index proposed by Baker, Bloom, and Davis (2016) to measure policy-related economic uncertainty in the United States. They establish the index by collecting and analyzing data from several sources, including the digital archives of 10 leading US newspapers (The New York Times and The Wall Street Journal), policy reports, and tax code revisions. The algorithm also quantified the frequency and tone of the articles' mentions of policy uncertainty with a focus on articles containing terms related to policy uncertainty, the economy, fiscal policy, monetary policy, and regulatory policy. The resulting monthly index captures significant events such as Gulf Wars, close presidential elections, and 9/11, among others. This index has been shown to have value in predicting future output and employment movements.

NPU - news-based policy uncertainty index from Baker, Bloom, and Davis (2016) is to capture policy-related economic uncertainty using data from 10 major newspapers (USA Today, the Miami Herald, the Chicago Tribune, the Washington Post, the Los Angeles Times, the Boston Globe, the San Francisco Chronicle, the Dallas Morning News, the Houston Chronicle, and the WSJ). Monthly searches are performed for terms related to economic and policy uncertainty. The raw count of relevant articles is divided by the total number of articles in each paper and month, then normalized for each paper with a unit standard deviation from Jan 1985 to Dec 2009. This index data is from the Economic Policy Uncertainty website.

$GEPU$ - global economic policy uncertainty index is proposed by Davis (2016), a monthly GDP-weighted average of economic policy uncertainty indices from 21 countries, including the US, from January 1997 onward. This index provides a comprehensive picture of the shocks affecting the U.S. economy by capturing its uncertainty as a whole and accounting for exogenous influences both globally and nationally.

VIX - the financial market volatility measure is an index created by the Chicago board options exchange, used to measure market expectations of near-term volatility. In Bloom (2009) study, monthly returns volatility are calculated using the daily S&P500 index's standard deviation normalized to the same mean and variance as the VIX index from 1986 onward. The VIX reacts more strongly to financial and stock market events such as the World.Com Fraud and the Lehman Brothers collapse. Bloom (2009) found that the VIX and the EPU often move together, with a correlation of 0.58, which is very close to what has been found in this paper 0.602.

BAA - the other financial measure, the corporate bond spread BAA, is the difference between the yields of BAA-rated corporate bonds and comparable-maturity Treasury bonds, reflects credit risk premiums demanded by investors. Sourced from the Federal Reserve Bank of St. Louis Fred website. Choi and Loungani (2015) reviewed the BAA spread literature, highlighting its use as a proxy for credit market conditions in various empirical studies. Caggiano, Castelnuovo, and Groshenny (2014) found that the BAA spread is a leading indicator of recessions, peaking before economic downturns. Reverse causality is a potential issue, as reduced consumption might result from negative economic outcomes rather than higher uncertainty.

$UMCS$ - University of Michigan Consumer Sentiment Index involves more of the household's responses than the others. this index measures consumer confidence in the United States through monthly phone surveys. Bloom (2009) describes the Michigan consumer uncertainty as a measure of consumers' perceived uncertainty about the future. This index, which has been increasingly referenced in the literature Leduc and Liu (2016), is cyclical and tends to rise during economic booms. In this paper, a negative sign is added to make this measure counter-cyclical, aligning it with the other measures.

C IV Regression with Various Uncertainty Measures

C.1 Estimating Uncertainty on Volatility

Specification

The state uncertainty measure may be endogenous to employment volatility if local newspaper search terms are influenced by local employment volatility. Introducing additional national uncertainty measures further reduces measurement errors with the following regression:

$$Y_{i,t} = \gamma_i + \theta N_t + \tau_{i,t}, \tag{15}$$

$Y_{i,t}$ represents the volatility of employment in the business cycle, quantified as the standard deviation of cyclical employment levels in state i over a rolling quarter-year window centered at time t. N_t represents the change in national economic uncertainty (ΔEPU and other measures). The term γ_i captures time-invariant state-specific factors, such as population size and cultural background. This variation ensures that the relationship between economic uncertainty and employment volatility arises from changes both across states and over time. θ is the coefficient of interest, representing the change in employment volatility associated with a one-percentage-point change in N_t.

Estimation Results

Table A.6 displays the regression results from Equation 15. Standard errors are reported using Newey-West. In Column 1, state-level $\Delta SEPU$ is instrumented with national-level ΔEPU; this IV regression is reported as a reference. Column 1 shows a positive and significant coefficient, indicating a strong correlation between $\Delta SEPU$ and employment volatility. Column 2 regresses national-level EPU on employment volatility directly. A positive and significant coefficient indicates that an one-unit increase in ΔEPU corresponds to a significant increase in volatility. Although Column 2 exhibits a larger coefficient, the F-value is lower without applying IV method. The following columns, reporting the regression results of employment volatility on $\Delta GEPU$, ΔNPU, ΔVIX, ΔBAA, and $\Delta UMCS$, show consistently positive and significant results, indicating that increased uncertainty is associated with higher volatility. The reported F-values are low overall, suggesting that besides economic uncertainty, there's substantial variation in cyclical employment volatility has not been explained by the model. Given the low F-values, the next section will explore the inclusion of demographics as a regressor.

Table A.6: Analyzing Various Economic Uncertainties and Employment Volatility

	(1) $\Delta SEPU$ IV	(2) ΔEPU OLS	(3) $\Delta GEPU$ OLS	(4) ΔNPU OLS	(5) ΔVIX OLS	(6) ΔBAA OLS	(7) $UMCS$ OLS
N_t	71.10***	102.1***	52.55*	34.38*	73.09**	191.6***	278.5**
	(14.25)	(35.45)	(29.19)	(20.83)	(31.21)	(73.34)	(109.5)
$F-stat.$	81.35	8.294	3.242	2.725	5.486	6.825	6.466
$Obs.$	3416	3416	3416	3416	3416	3416	3416

Note: This table displays the regression results for cyclical employment volatility to various uncertainty measures following Equation 15 across US states from 2000Q1 to 2017Q4. The coefficients on uncertainty measures are all positive and significant. The results suggest that higher economic uncertainty is associated with higher cyclical employment volatility regardless of the measurements. All regression incorporates state fixed effects and applies Newey-West standard errors.

C.2 Role of Age Demographics

Specification

The second stage regression with national uncertainty measures is as follows:

$$Y_{i,t} = \gamma_i + \eta_1 N_t + \eta_2 (D_{i,t} - \overline{D}) * (N_t - \overline{N}) + \eta_3 D_{i,t} + \nu_{i,t}, \tag{16}$$

The first stage equation with age structure instrumented by lagged birth rates is as follows:

$$D_{i,t} = \gamma_i + \zeta_1 B_{i,t-k} + \zeta_2 (B_{i,t-k} - \overline{B}) * (N_t - \overline{N}) + \zeta_3 N_i + \varrho_{i,t}, \tag{17}$$

Estimation Results

Table A.7 displays the regression results following Equation 16. Throughout the columns, the dependent variable is the standard deviation of state-level cyclical employment, $Y_{i,t}$. Independent variables include the growth rate of various national economic policy uncertainties N_t, which can be ΔEPU, $\Delta GEPU$, ΔNPU, ΔVIX, ΔBAA, and $\Delta UMCS$. The results were obtained by instrumenting age shares with their respective lagged birth rates while also including state fixed effects. Standard errors are reported using Newey-West with one lag. The regression replicates the baseline regression, incorporating both

$Prime$ and $Young$, along with their interactions with various uncertainty measures; the reference group is the Old group and its interaction with N_t.

Row 1 reports the coefficients on the interaction of various N_t interacted with the $Prime$ share, while row 2 reports the coefficients on various N_t. Across all columns, the coefficients on N_t (Row 2) are consistently significant and positive, indicating a positive correlation between the various economic uncertainty and the increase in employment volatility. However, the coefficients on the interaction term (Row 1) are only significant in the first column, indicating that prime age share significantly affects the EPU impact on state employment volatility, whereas this effect is not significant in the following columns. This can be explained in several ways: one reason might be that different economic uncertainty measures capture different economic characteristics. The local labor market in the US responds more to national policy-related uncertainty and not as much to other news-related, financial-related, or consumption sentiment-related uncertainties. Nevertheless, the consistent negative sign across the columns indicates that a higher prime share is associated with lower uncertainty-driven volatility overall, which is consistent with the previous findings.

Table A.7: Analyzing the Role of Demographics with Various Uncertainty Measures

	(1) ΔEPU	(2) $\Delta GEPU$	(3) ΔNPU	(4) ΔVIX	(5) ΔBAA	(6) $\Delta UMCS$
$N_t * Prime$	-75.46**	-26.13	-21.07	-158.2	-274.6	-506.1
	(34.11)	(26.53)	(20.14)	(260.1)	(268.8)	(468.8)
N_t	116.6***	61.83***	37.81***	46.84	202.7***	167.2**
	(27.51)	(22.55)	(14.11)	(35.35)	(70.31)	(72.41)
$F-stat.$	61.23	69.06	69.16	43.65	43.98	46.28
$Obs.$	3416	3416	3416	3416	3416	3416

Note: This table presents regressions using quarterly data from 2000Q1 to 2017Q4 across states. The dependent variable is cyclical employment volatility. Column 1 adapts the format of Equation 6, replacing $\Delta SEPU$ with various national economic uncertainty measures. Detailed documentation of this equation can be found in the main content. All regressions incorporate state fixed effects and utilize Newey-West standard errors.

D Dynamic Responses with Various Uncertainty Measures

D.1 Estimating Uncertainty on Volatility

Specification

This section examines employment volatility in response to various national N_t shocks using various measures following the LP framework introduced by Jordà (2005). The cumulative IRF regression equation is presented as follows:

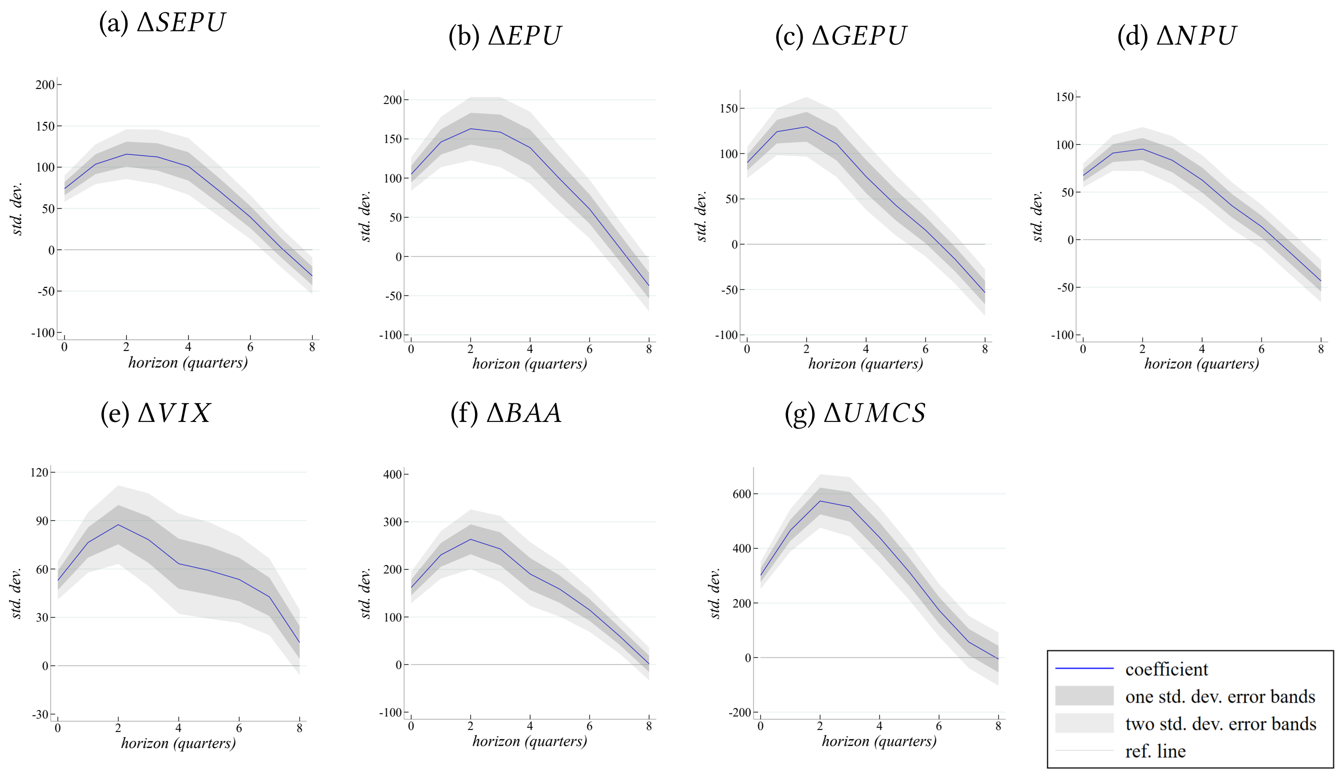
$$Y_{i,t+h} = \eta_i^h + \zeta_1^h N_t + \zeta_2^h \sum_{s=1}^{2} N_{t-s} + \zeta_3^h \sum_{s=1}^{2} Y_{i,t-s} + \kappa_{i,t+h}, h = 0, 1, ..., H \tag{18}$$

$Y_{i,t+h}$ represents the dependent variable: the cumulative change in employment volatility from time t to $t+h$. This illustrates the responses of volatility at each period over H periods following an uncertainty shock. Volatility is calculated as the standard deviation of a centered nine-quarter rolling window of cyclical employment. The regression includes two previous periods of state employment volatility ($Y_{i,t-s}^h$), two prior periods of uncertainty measures (N_{t-s}^h), and state fixed effects (κ_i^h). The primary variable of interest is ζ_1^h, which quantifies the standard deviation change in employment volatility from time t to $t+h$ following an uncertainty shock at time t.

Estimation Results

Figure A.1 presents estimates of ζ_1^h with plus/minus one and two Newey and West (1987) standard error bands for $h = 0, 1, \ldots, 8$ quarters for each uncertainty shock. Figure (a) reports the responses on employment volatility following a one percentage point increase in state $\Delta SEPU$, where the $\Delta SEPU$ is instrumented with ΔEPU. This dynamic response is reported as a reference, with the following ones reporting the dynamic responses following a one percentage point increase in ΔEPU, $\Delta GEPU$, ΔNPU, ΔVIX, ΔBAA, and $\Delta UMCS$ separately. Following an uncertainty shock (across different measures), employment volatility increases, reaching a peak two quarters later, and then gradually decreases, while the positive effect persists for most of the horizons. These results are consistent across different uncertainty measures from Figures (a) to (g).

Figure A.1: Response of Employment Volatility to Various Uncertainty Measures



Note: The figures depict LP-IV IRF of cumulative cyclical employment volatility in response to various uncertainty measures following Equation 9. They illustrate the dynamic responses in employment volatility to a one percentage point increase in the corresponding economic uncertainty. The vertical axes depict changes in standard deviations of employment volatility relative to the origin. Grey areas represent one and two Newey-West standard deviation confidence bands for each coefficient estimate.

D.2 Role of Age Demographics

The dynamic second stage regression form is as follows when the role of age structure is evaluated using various national-level uncertainty measures:

$$Y_{i,t+h} = \eta_i^h + \phi_1^h N_t + \phi_2^h[(D_{i,t} - \overline{D}) * (N_t - \overline{N})] + \phi_3^h D_{i,t}$$
$$+ \phi_4^h \sum_{s=1}^{2} N_{t-s} + \phi_5^h \sum_{s=1}^{2}[(D_{i,t-s} - \overline{D}) * (N_{t-s} - \overline{N})] + \phi_6^h \sum_{s=1}^{2} Y_{i,t-s} + \iota_{i,t+h}, h = 0, 1, ..., H \; , \tag{19}$$

where explanatory variables are defined the same with earlier IV two-stage equations. η_i^h captures the state fixed effect from time t to $t+h$. ϕ_1^h measures the effect from the current period of economic policy uncertainty from time t to $t+h$. ϕ_2^h reports the estimate for the interaction between the demeaned terms, $(D_{i,t} - \overline{D}) \times (U_{i,t} - \overline{U})$, from t to $t+h$. ϕ_3^h reports the direct demographic impact, which is not the coefficient of interest. Following the previous IV strategy, $D_{i,t}$ is instrumented by birth rates $B_{i,t}$ to address endogeneity concerns. The primary variables of interest are ϕ_1^h, which captures the direct impact of $\Delta SEPU$ on volatility, and ϕ_2^h, which captures the demographic effects of uncertainty-driven volatility.

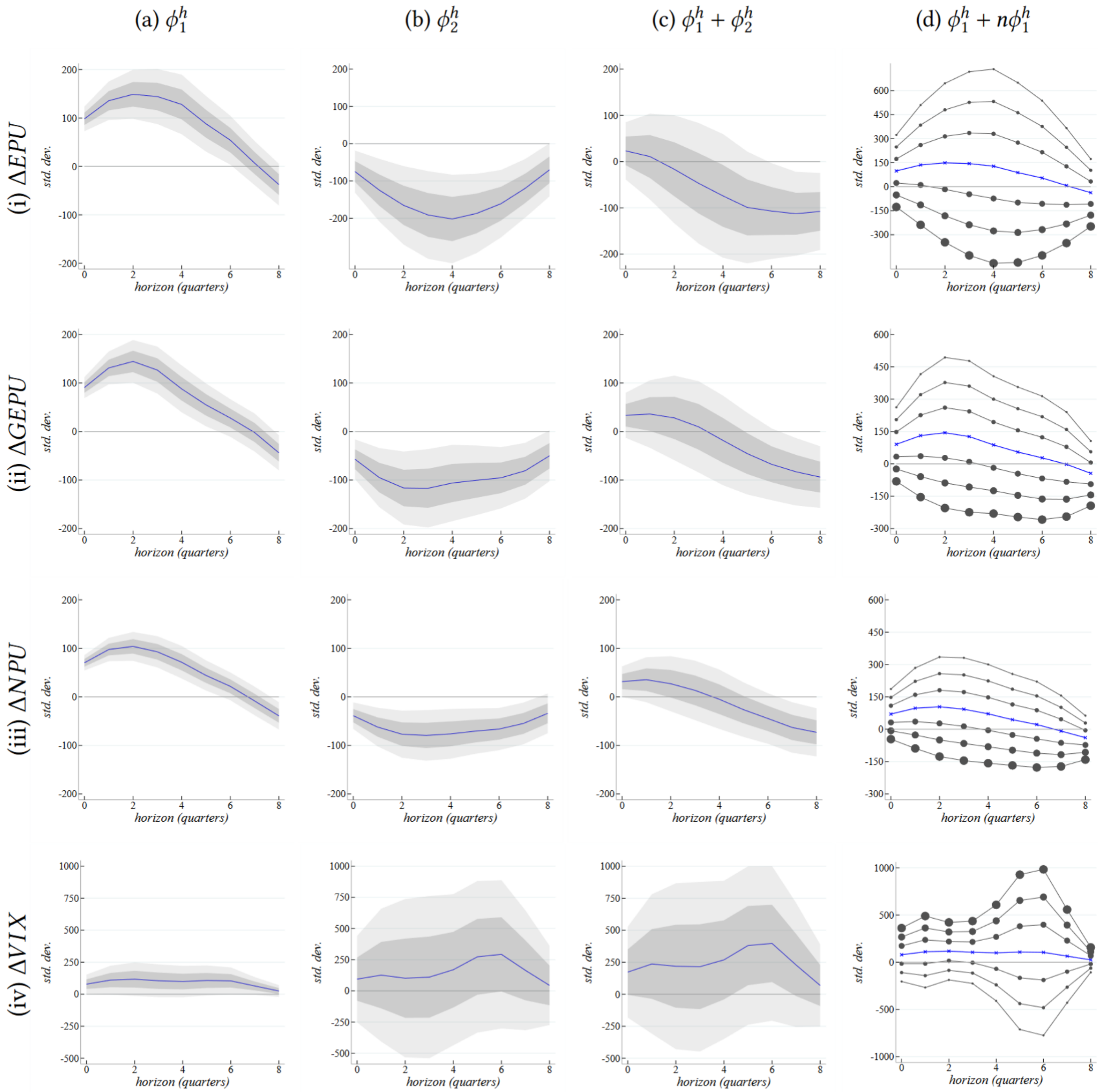
Estimation Results

Figure A.2 reports the previous baseline LP-IV regression using various national uncertainty indicators, including ΔEPU $\Delta GEPU$, ΔNPU, ΔVIX, ΔBAA, and $\Delta UMCS$. The results compare states with two working-age groups: those with a larger prime share relative to the sample average and those with an older share compared to the sample average. The results are reported with plus/minus one and two Newey and West (1987) standard error bands for $h = 0, 1, \ldots, 8$ for each uncertainty shock.

Column 1 displays the N_t effect for states with typical working-age distributions. Column 2 evaluates the change in effect of the prime share on the impact of uncertainty if states contain one percentage point higher of prime than old. Column 3 presents the total uncertainty impact on employment volatility for eight quarters considering the higher share of prime relative to the sample average compared to that of old. Meanwhile, Column 4 estimates the uncertainty impact on states that deviate by one, two, or three percentage points from the average prime share relative to old.

Interestingly, different types of uncertainty show diverse patterns. Economic policy-related or news-related uncertainty (including ΔEPU, $\Delta GEPU$, and ΔNPU), as well as consumer sentiment ($\Delta UMCS$), show the regression results that align with the main results: A higher share of prime associates with significantly reduced effects in uncertainty-induced volatility. Conversely, this result is either reversed or muted for financial market uncertainty measures, including ΔVIX and ΔBAA. Here, a higher share of prime correlates with increased financial uncertainty-induced volatility (in Column v), or a higher share of prime has no impact on volatility (in Column vi). Either result is opposite to the main findings. This observation can be explained by considering the distinctions between these measures. Further research could dig into the reasons behind this diverse pattern across the effects of economic uncertainties.

Figure A.2: Response of Employment Volatility to Age Distribution and Various Uncertainty Measures



Note: The figures display the LP-IV IRF of cumulative cyclical employment volatility in response to various uncertainty measures that compares the effect from prime relative to that from old. The vertical axes are changes in standard deviations of employment volatility. The grey areas indicate one and two Newey-West standard deviation confidence intervals for each coefficient estimate.

E Regressions With Controls

This section addresses potential confounding variables that might influence the relationship between age structure and uncertainty-driven employment volatility. Subsequent regression analysis includes these variables as controls.

E.1 Summary Statistics

Table A.8 provides summary statistics of controls from various sources. Demographic and education data is from the IPUMS-Current Population Survey (CPS). The variables are constructed following CPS variable dictionary, with quarterly ones derived from monthly averages. These variables are constructed without applying CPS weights. State income data, including personal income and sectoral incomes (e.g., manufacturing, retail trade, transportation, and healthcare), are collected from the Bureau of Economic Analysis (BEA). All incomes are adjusted using CPI with 1982-84 as the base year. Individual income (adjusted for inflation), state welfare-program programs, and political climate data are collected from the University of Kentucky Center for Poverty Research and linearly interpolated to match quarterly dataset.

Table A.8: Summary Statistics for Control Variables

	Mean	Min	Max	SD	N
Demographics					
$femar$	31.01	21.34	36.44	1.80	3416
$fework$	24.37	18.71	32.05	1.95	3416
$white$	83.00	29.58	98.63	10.89	3416
$black$	10.98	0.00	66.52	11.10	3416
$immigrant$	4.77	0.04	18.43	3.29	3416
$hisp$	9.97	0.20	49.15	10.11	3416
$hrwork$	38.87	36.11	41.51	0.78	3416
$lwskill$	58.20	35.50	73.03	5.35	3416
Education					
$lesshigh$	13.79	6.82	23.51	2.89	3416
$higschool$	24.01	12.11	37.13	3.52	3416
$somecollege$	21.17	9.72	29.23	2.87	3416
$college$	13.41	5.98	25.72	2.77	3416
$grad$	7.21	2.74	30.10	3.01	3416
Sectoral Income					
$persona\,lincome$	1,206,423	95,243	9557,959	1,391,595	3416
$wage\,salary$	626,320	48,016	4,967,020	723,268	3416
$constrcut$	54,008	3,361	452,084	62,023	3400
$manufact$	95,319	-67.97	746,985	105,235	3404
$retail\,trade$	55,173	3,061	409,413	62,867	3416
$transport$	31,235	1,667	229,932	35,365	3400
$health$	90,913	5,114	649,032	98,601	3416
Individual Income					
$totalpersonal$	25,723	18,118	41,560	2,758	3416
$wageandsalary$	23,451	16,045	38,723	2,549	3416
$non-farmbusiness$	107.18	-106.02	1,641	147.53	3416
$welfare/publicassistance$	13.37	0.00	233.36	19.31	3416
$retirement$	332.77	0.00	2,736	263.04	3416
$unemploymentbenefit$	125.05	0.00	1,141	97.94	3416
Welfare Policies					
$foodinsecure$	13.54	3.27	25.22	3.37	3416
$grossstateproduct$	307,104	18,013	2,939,071	374,929	3416
$workers'compensation$	298,834	4,220	3,507,711	530,654	3416
$povertyrate$	12.84	4.50	23.10	3.32	3416
$stateEITCrate$	0.07	0.00	0.85	0.11	3416
$stateminwage$	6.69	2.65	12.81	1.39	3416
$medicaidbeneficiaries$	1,126,960	45,141	12,656,781	1,499,903	3416
Political Climate					
$governorisdemocrat(1 = Yes)$	0.44	0.00	1.00	0.48	3344
$numberinlowerhousedemocrat$	57.01	8.00	239.00	32.00	3272
$numberinlowerhouserepublican$	57.14	6.00	296.00	33.95	3272

Note: This table summarizes the control variables, including state demographics and education levels from IPUMS-CPS, sectoral income from BEA, individual income, welfare program incomes, and political climate from Center for Poverty Research. The sample ranges from 2000Q1 to 2017Q4 for forty-eight states including DC.

E.2 Specification of Regression with Controls

The following is the second-stage regression equation, considering controls:

$$Y_{i,t} = \gamma_i + \lambda_1 U_{i,t} + \lambda_2 (D_{i,t} - \overline{D}) * (U_{i,t} - \overline{U}) + \lambda_3 D_{i,t} + \lambda_4 (C_{i,t} - \overline{C}) * (U_{i,t} - \overline{U}) + \lambda_5 C_{i,t} + \varepsilon_{i,t}, \tag{20}$$

where $C_{i,t}$ stands for various controls including variables of state demographics, education, income types, welfare policies, and state political climate. The following will discuss each group of the controls and their associated results.

E.3 Controlling Education

Prior research examined education when studying labor market outcomes. For instance, Hoynes, Miller, and Schaller (2012) includes less-educated men to study cyclic variations. Mennuni (2019) shows a correlation between demographics with a higher education and reduced business cycle volatility. Building on the earlier work, this paper includes education levels when investigating the effect of age demographics on employment volatility induced by economic uncertainty. Results are presented in Table A.9.

Table A.9: Regression with Education

	(1)	(2)	(3)	(4)	(5)	(6)
$U_{i,t}$	84.93***	101.4***	84.90***	80.37***	82.58***	82.88***
	(21.09)	(26.59)	(20.34)	(19.05)	(19.37)	(19.62)
$U_{i,t} * Prime$	-48.38**	-79.07*	-42.50***	-52.87**	-38.84**	-42.93***
	(21.18)	(40.34)	(16.18)	(25.12)	(16.01)	(16.25)
$U_{i,t} * lesshigh$		26.95				
		(16.53)				
$U_{i,t} * higschool$			-4.434			
			(5.043)			
$U_{i,t} * somecollege$				-21.08*		
				(12.60)		
$U_{i,t} * college$					6.236	
					(4.910)	
$U_{i,t} * grad$						2.693
						(5.014)
$F - stat.$	49.19	42.69	49.52	50.57	51.21	49.31
$Obs.$	3416	3416	3416	3416	3416	3416

Note: This table presents the results of the baseline regression with different education level variables.

The first column provides the baseline from the main content for reference. Across the subsequent columns, the main findings remain consistent across various education controls. Notably, controlling for education variables of less than high school and some college is associated with a more sizable prime age effect on economic uncertainty impact (in Row 2); conversely, controlling for high school, college, and graduate degree correlates with a smaller magnitude of the prime age effect on uncertainty impact.

E.4 Controlling Individual Income

This subsection investigates the prime impact with a range of individual income measures for state residents. Results are presented in Table A.10. The first column reports the baseline regression, and subsequent columns include each one of the income measures. Across columns, controlling for total, total wage, and total business income is associated with a smaller coefficient for the prime effect on uncertainty impact (in Row 2). Conversely, controlling for welfare, retirement, and unemployment income yields a larger coefficient in Row 2.

Table A.10: Regression with Individual Income

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$U_{i,t}$	84.93***	86.52***	86.90***	84.30***	85.74***	84.78***	88.45***
	(21.09)	(21.48)	(21.55)	(20.96)	(21.60)	(21.10)	(22.50)
$U_{i,t} * Prime$	-48.38**	-43.62**	-43.42**	-48.04**	-50.04**	-48.77**	-51.94**
	(21.18)	(18.56)	(18.57)	(20.92)	(22.76)	(22.05)	(23.62)
$U_{i,t} * inctot$		0.0122					
		(0.00795)					
$U_{i,t} * incwage$			0.0163*				
			(0.00950)				
$U_{i,t} * incbus$				-0.0181			
				(0.114)			
$U_{i,t} * incwelfr$					0.805		
					(0.954)		
$U_{i,t} * incretir$						-0.00988	
						(0.0551)	
$U_{i,t} * incunemp$							-0.103
							(0.179)
$F-stat.$	49.19	48.12	48.40	47.90	47.15	47.39	47.16
$Obs.$	3416	3416	3416	3416	3416	3416	3416

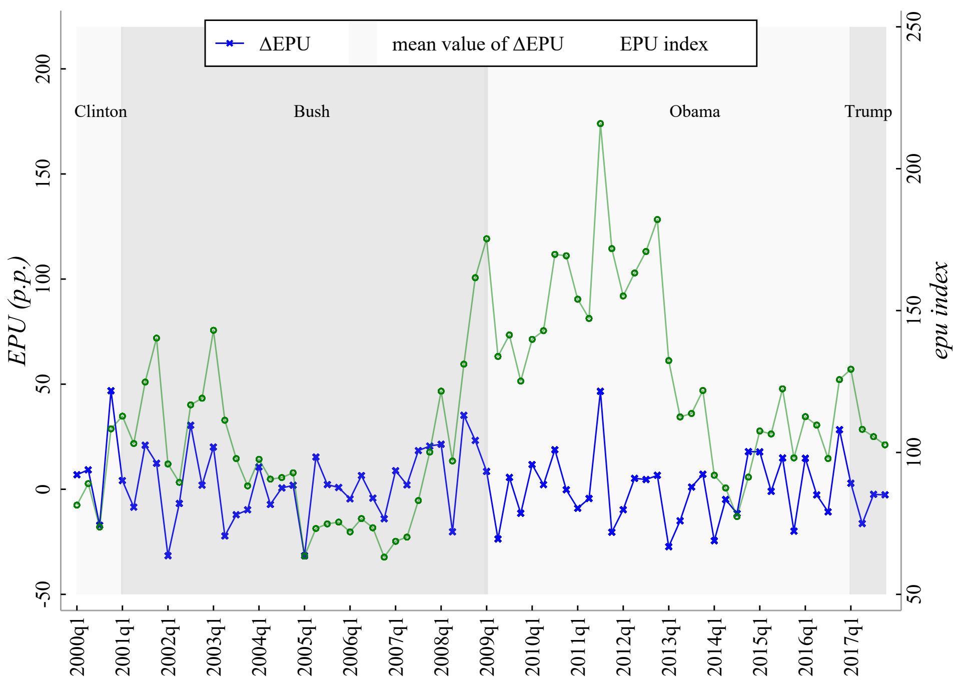
Note: This table presents the results of the baseline regression with different individual income variables.

E.5 Controlling Welfare Programs and Political Climate

This subsection examines the variations in state transfer incomes and political climates impacts on the age structure's effect on labor markets. As depicted in Figure A.3, one can observe a lower level of EPU (in green) with minor percentage changes (in blue) during the Republican presidencies of Bush and Trump. In contrast, there's a higher level of EPU with more significant changes during the Democratic presidencies, specifically the Clinton and Obama periods. The author suspects that state transfer income and political environment could be the confounding effect that impacts the age structure's effect on uncertainty-driven labor market volatility. The regression with various welfare and political measures is in Table A.11.

The finding is consistent with baseline, except for the regression results including Gross State Product (GSP) in the third column: when GSP is controlled, the significance of λ_2 disappears. However, the interpretation of this may not imply that GSP is the causal mechanism; instead, GSP could be an outcome influenced by both local age structure and uncertainty levels. Thus, controlling for GSP may lead to over-controlling, removing the causal effect of age and uncertainty and rendering insignificance. Across the other columns, the coefficients on the prime interaction term (in Row 2) are smaller when controlling for worker compensation and number of Medicaid beneficiaries, while controlling for other variables is associated with a larger coefficient compared with that in the baseline.

Figure A.3: Economic Uncertainty Measure Plots with Presidency



Note: This figure depicts the EPU index and ΔEPU with the presidency from 2000-2017 checked in the background.

Table A.11: Regression with Welfare Policies and Political Climate

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$U_{i,t}$	84.93***	76.78***	71.40***	77.48***	86.76***	82.67***	79.29***	84.19***	87.51***	93.20***	74.01***
	(21.09)	(23.54)	(13.97)	(17.11)	(21.42)	(20.09)	(19.37)	(20.82)	(20.93)	(26.27)	(14.71)
$U_{i,t} * Prime$	-48.38**	-52.60*	-12.85	-30.80**	-50.74**	-49.16**	-50.43**	-48.97**	-48.48**	-100.3*	-17.21*
	(21.18)	(27.18)	(8.173)	(13.51)	(21.96)	(20.55)	(21.25)	(20.49)	(20.08)	(51.83)	(9.028)
$U_{i,t} * foodinscr$		-1.835									
		(8.722)									
$U_{i,t} * stateproduct$			0.000179*								
			(0.000105)								
$U_{i,t} * wrkcompenst$				0.000122*							
				(0.0000645)							
$U_{i,t} * povertyrt$					-0.964						
					(5.065)						
$U_{i,t} * governordm$						51.28					
						(36.30)					
$U_{i,t} * nlowhousedm$							1.199*				
							(0.726)				
$U_{i,t} * nlowhouserp$								0.181			
								(0.377)			
$U_{i,t} * EITCrate$									-92.72		
									(114.7)		
$U_{i,t} * minimumwage$										-62.73	
										(43.04)	
$U_{i,t} * medicaidbnfcr$											0.00004
											(0.000029)
$F-stat.$	49.19	47.33	53.84	55.55	46.24	47.53	48.53	49.49	47.63	40.10	51.87
$Obs.$	3416	3416	3416	3416	3416	3344	3272	3272	3416	3416	3416

Note: This table presents the results of the baseline regression with different welfare program and political climate variables.

F Alternative Regression Specifications

This subsection considers a series of robustness checks for the baseline regression results using different regression specifications. In Table A.12, the first column presents the baseline results for reference. Column 2 incorporates all three age groups as controls and excludes the constant to avoid multicollinearity. In this regression, $\Delta SEPU$ in Column 1 is significant at the 90% level. Meanwhile, its interaction with prime in Column 2 also shows significance, with a coefficient of -54 — this is consistent with the baseline findings but has marginally larger coefficients. Column 3 clusters the standard errors at the state level instead of reporting Newey-West robust standard errors. While the result in this column retains significance, the diminished F-statistics hint at potential HAC concerns. This observation supports the use of HAC standard errors in the main regressions.

In Column 4, the OLS regression results indicate the coefficient on the prime interaction term (Column 2) dropping to -0.67 and losing its significance. This finding might suggest that as prime-aged workers move to states with higher volatility for better job opportunities, the demographic reduction effect of prime on uncertainty impact vanishes. However, using lagged birth rates as an instrument addresses this bias and counters the potential issues with OLS estimates, validating the primary regression specification. The last column contrasts the effects of prime demographics with those of young, revealing that states with a larger prime population experience reduced volatility, albeit not statistically significant. In summary, the aforementioned results reinforce the primary findings that prime aids in counteracting the effects of uncertainty-induced volatility.

Table A.12: Regression with Alternative Regression Specifications

	(1) Baseline IV	(2) Control ages IV	(3) Cluster state IV	(4) OLS	(5) Prime -young IV
$U_{i,t}$	86.94***	90.37***	86.94***	13.01***	77.43***
	(21.90)	(22.38)	(25.14)	(5.012)	(15.67)
$U_{i,t} * Prime_{i,t}$	-48.38**	-54.13**	-48.38**	-0.666	-15.40
	(21.18)	(21.58)	(20.25)	(1.568)	(13.88)
$Young_{i,t}$	✓	✓	✓	✓	
$Prime_{i,t}$	✓	✓	✓	✓	✓
$Old_{i,t}$		✓			✓
$U_{i,t} * Young_{i,t}$	✓	✓	✓	✓	
$U_{i,t} * Old_{i,t}$					✓
$F - stat.$	49.19	111.3	3.258	77.94	137.6
$Obs.$	3416	3416	3416	3416	3416

Note: The dependent variable in this table is cyclical employment volatility. Column 1 shows the baseline. Column 2 incorporates the young age share based on Column 1, omitting the constant to avoid multicollinearity. Column 3 clusters standard errors at the state level. Column 4 undertakes an OLS regression. Column 6 presents the IV regression on both prime and old, including their interaction with $\Delta SEPU$, thus treating young as the omitted reference group. All columns include state fixed effects.

Table A.13: IV Regression with Various Outcome Specifications

	(1) Center-17	(2) Center-13	(3) Center-9	(4) Center-5	(5) Backward-17	(6) Forward-17
$U_{i,t}$	84.93***	71.79***	47.40**	45.88***	44.79***	47.70**
	(21.09)	(21.87)	(21.16)	(16.70)	(17.22)	(22.14)
$U_{i,t} * Prime$	-48.38**	-36.90*	-22.17	-17.62	-26.74	-60.79***
	(21.18)	(22.26)	(21.63)	(16.85)	(18.17)	(20.97)
$F - stat.$	49.19	38.54	31.71	23.49	45.56	40.00
$Obs.$	3416	3416	3416	3416	3416	3024

Note: This table presents the results of the baseline regression with various outcome specifications for robustness checks. The first column details the baseline regression where volatility is calculated using a center-17-quarter window. Subsequent columns (columns 2 to 4) report on volatility determined over different quarter lengths (5, 9, and 13) employing a centered rolling window. The last two columns utilize both backward and forward 17-quarter rolling windows.

G Different Outcome Specifications

G.1 For IV Estimation

Within the main context of this paper, employment volatility is defined as the standard deviation of a state's employment level during a centered 17-quarter rolling window in IV regression. In the following, the analysis utilizes centered windows of different lengths, including 5-quarter, 9-quarter, and 13-quarter windows, for the robust regression analyses. In addition, backward windowed and forward windowed volatility measurements are also incorporated into the subsequent regression. To be more specific, the forward17-quarter window incorporates employment data from the current quarter along with the succeeding 16 quarters.

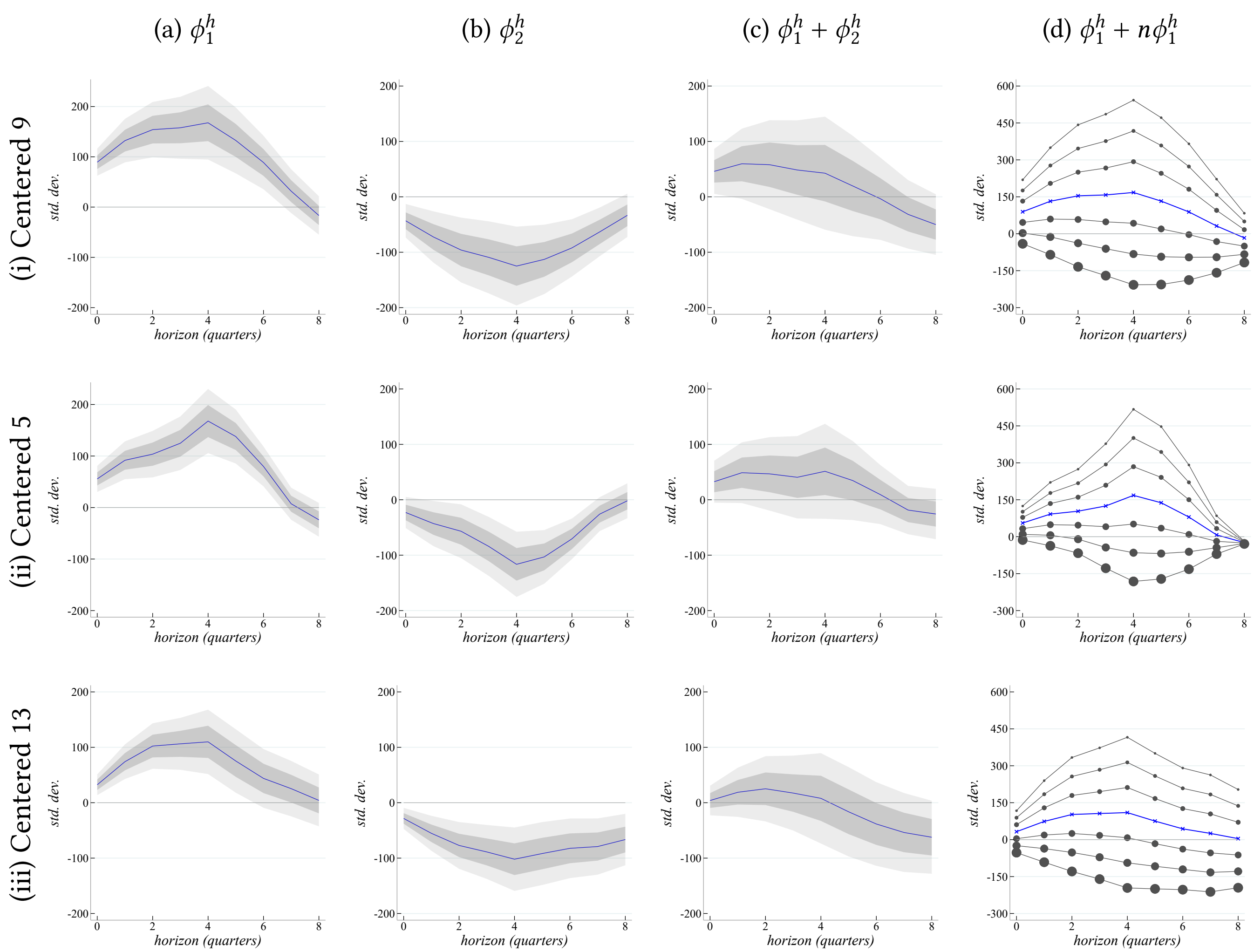
The IV regression results with the various outcome variable specifications are presented in Table A.13. Overall, the results remain consistent, with significance experiencing changes when specifying the outcome variable of interest in different ways. Specifically, when employing a 13-quarters, 9-quarter to 5-quarter center window, both the magnitude and significance of the coefficient on the $U_{i,t} * Prime$ diminish with the decreasing number of windows incorporated in the outcome construction. However, the backward-17-quarter specification (Column 5) does not yield significant results, which can be interpreted as the employment volatility from the last four years may be driven by many other economic factors other than the current economic uncertainty. With the forward-17-quarter approach (Column 6), the coefficient's magnitude remains sizable and is significant at 1%. Across the columns, all outcome variable specifications show positive and significant coefficients on economic uncertainty impact (in Row 1) and negative and sizable coefficients on prime interaction term (in Row 2). This result is consistent with the baseline results.

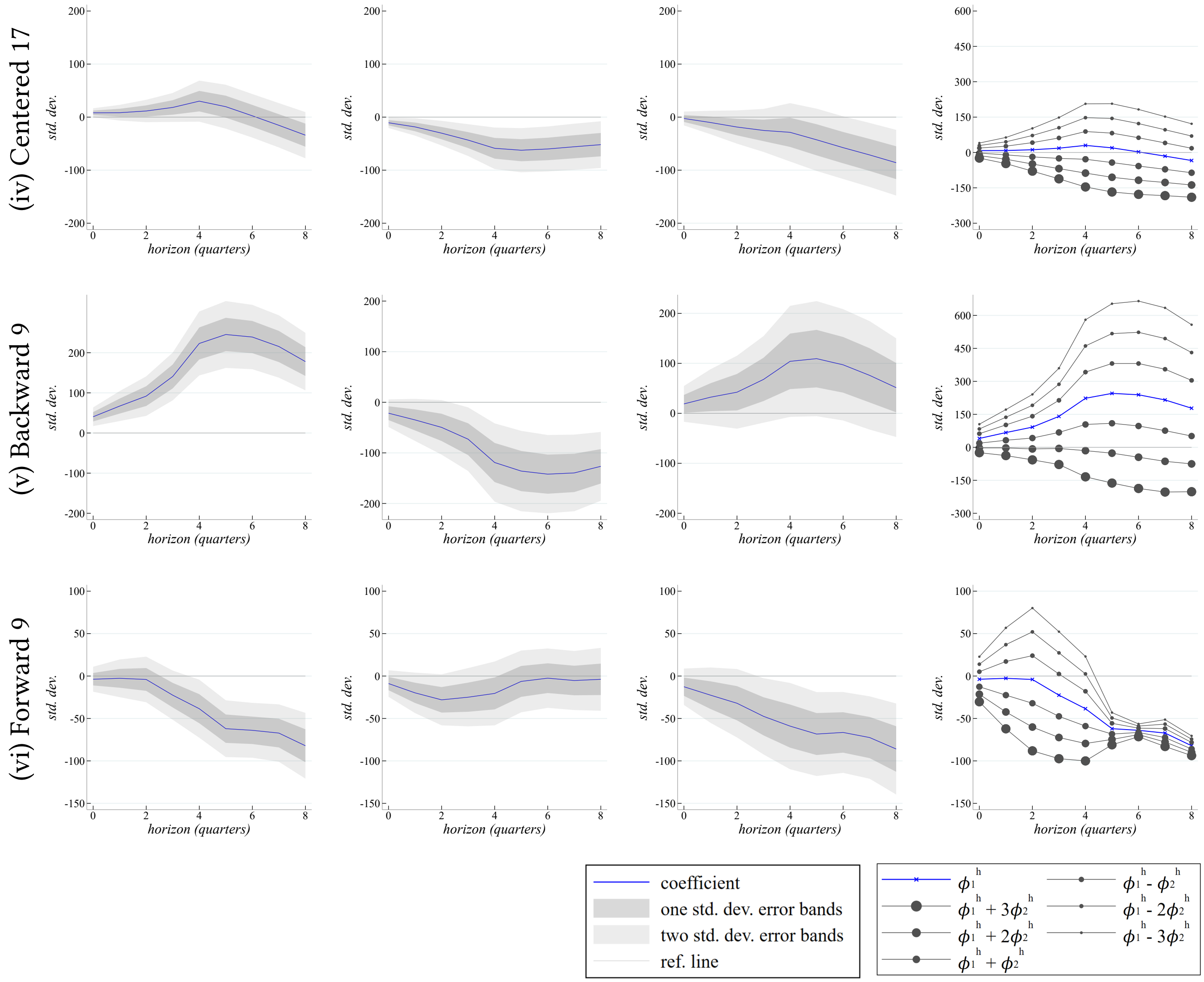
G.2 For LP-IV Estimation

Similarly, in the subsequent LP-IV dynamic regression, employment volatility is defined as the standard deviation of a state's employment level during centered-5, -13, and -17 quarters, as well as backward 9-quarter windowed and forward 9-quarter windowed volatility. Results are displayed in Figure A.4.

The dynamic responses of employment volatility following different outcome specifications show consistent results with the main dynamic regression of interest: Column 1 indicates a higher uncertainty shock associates with higher employment volatility for a national average age structure. Column 2 shows the amount of decrease in uncertainty when considering age deviations from the national average. Column 3 shows the lower total uncertainty impact for states with one percentage point higher share of prime compared to old. The last columns illustrate the age heterogeneity effect on uncertainty-induced volatility for states with one, two, and three percentage points share deviations from the national average age structure. Overall, a higher share of prime relative to old associates with a lower level of employment volatility, which supports the main dynamic estimation results.

Figure A.4: Response of Employment Volatility with Various Outcome Specifications



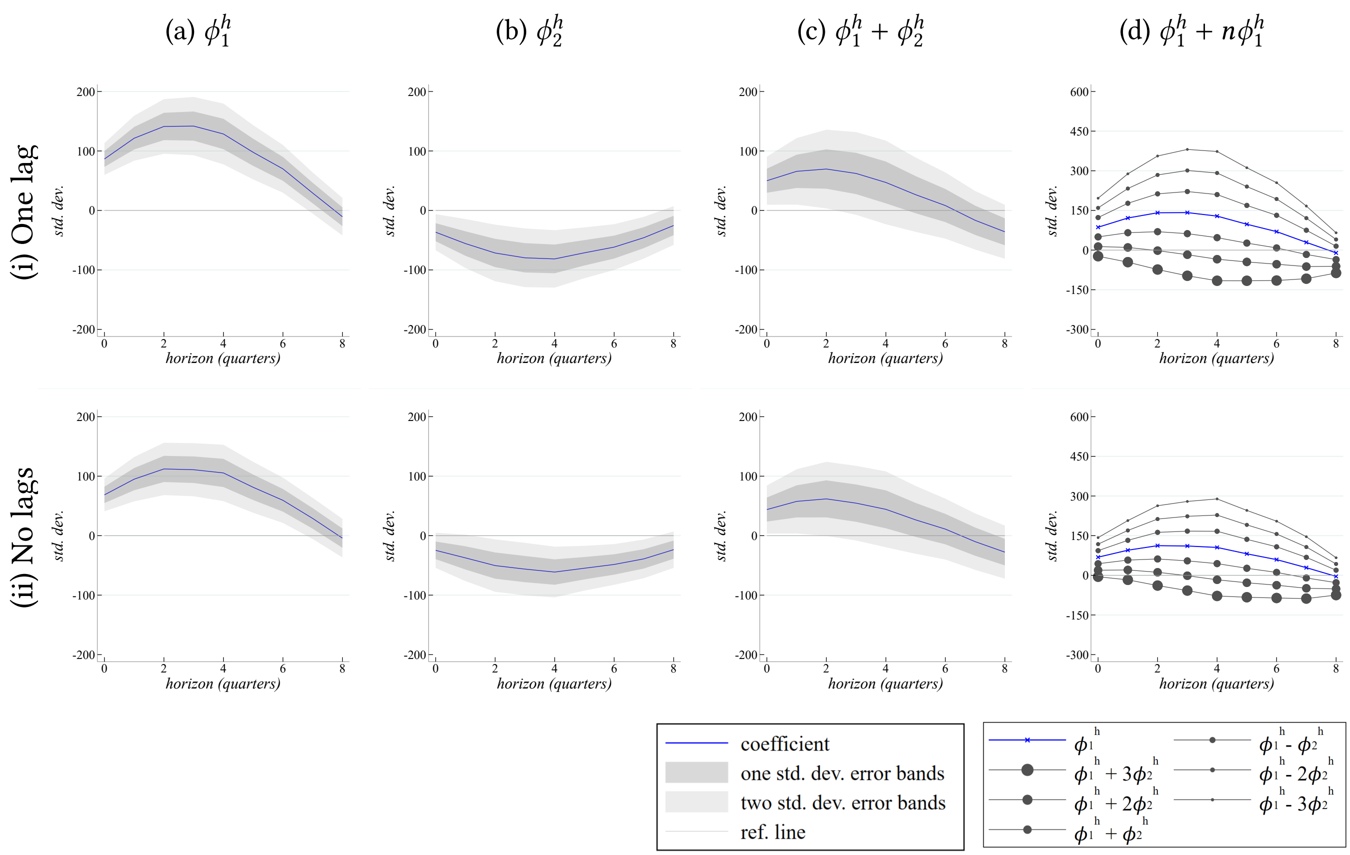


Note: The figures display the LP-IV IRF of cumulative cyclical employment volatility in response to state policy uncertainty shock that compares the effect from prime relative to that from old. The outcome variable is constructed using various numbers of windows and different calculations. Row i reports the baseline LP-IV result as a reference, with Row ii-vi reporting the dynamic responses on outcome variables constructed following centered five, thirteen, and seventeen quarters, as well as backward and forward nine quarters. The vertical axes illustrate changes in standard deviations of employment volatility. The grey areas indicate one and two Newey-West standard deviation confidence intervals for each coefficient estimate.

H Including different number of lags in LP-IV Estimation

The main content utilizes two lags of uncertainty, interaction, and volatility as independent variables when investigating the dynamic responses of employment volatility, following previous literature such as Cloyne, Jordà, and Taylor (2020). To demonstrate the robustness of the results, LP-IV regressions with no lag and one lag of the above variables are conducted, and the results are presented below in Figure A.5. Row i reports the dynamic responses on employment volatility when there is one lag of uncertainty, interaction, and volatility, while Row 2 shows the dynamic responses without any lags. The vertical axes illustrate changes in standard deviations of employment volatility. Overall, the preliminary results hold, with the coefficient size decreasing along with fewer numbers or no lags.

Figure A.5: Response of Employment Volatility with Various Lags in Outcome Variable



Note: The figures display the LP-IV IRF of cumulative cyclical employment volatility in response to state policy uncertainty shock that compares the effect from prime relative to that from old. Row i reports the dynamic responses on employment volatility when there is one lag of uncertainty, interaction, and volatility, while Row 2 shows the dynamic responses without any lags. The vertical axes illustrate changes in standard deviations of employment volatility. The grey areas indicate one and two Newey-West standard deviation confidence intervals for each coefficient estimate.

Table A.14: Data Source

	Source	Link
Quarterly State and Sectoral Income	Bureau of Economic Analysis	https://apps.bea.gov/iTable/?reqid=70&step=1&acrdn=2
Employment, Unemployment, and Labor force Participation	Bureau of Labor Statistics	https://data.bls.gov/PDQWeb/la
Job Gains and Job Loss	BLS Business Employment QCEW Dynamics and Job Openings	https://www.bls.gov/data/
Population Age	Census-Population Estimate Program	https://www2.census.gov/programs-surveys/popest/datasets/
birth rates 1936-2003	Center of Disease Control Vital Statistics	https://www.cdc.gov/nchs/products/vsus.htm
birth rates 2004-2022	Vital Statistics	https://wonder.cdc.gov/natality.html
Economic Uncertainty Measures	Economic Policy Uncertainty website	https://www.policyuncertainty.com/hrs_monetary.html
Moody's Baa Corporate Bond Yield	FRED	https://fred.stlouisfed.org/series/DBAA
CBOE Volatility Index	FRED	https://fred.stlouisfed.org/series/VIXCLS
Survey of Consumers	University of Michigan	http://www.sca.isr.umich.edu/
State Welfare Programs	University of Kentucky Center for Poverty Research	https://cpr.uky.edu/
State Demographics and Income	IPUMS- Current Population Survey	https://cps.ipums.org/cps/