Economic Uncertainty's Impact on Aggregate Employment Fluctuations: Estimating the Importance of the Population's 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. In particular, the volatility in employment due to uncertainty is lower in US states that have a higher population of prime-aged workers. This finding comes from a series of regressions using a quarterly panel of state data from 2000 to 2017. To address potential endogeneity, the current age distribution is instrumented by past birth rates, and state-level uncertainty is instrumented by national uncertainty. The regression estimates indicate that the reduction in employment volatility within states with a higher share of prime-age workers is quantitatively large. The results are robust across a battery of approaches, including using alternative variable definitions and model specifications, analyzing a host of state-level controls, using local projections to examine the dynamics, and accounting for the role of labor fluctuations in job losses and participation volatility.

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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 (15-65 years) from 2001 to 2017. In contrast, Figure 2 highlights the increasing percentage of older workers (aged 55-65). 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 level of uncertainty around future aggregate conditions has real effects on the macroeconomy, including GDP growth, inflation, and labor-market conditions (Baker, Bloom, and Davis (2012); Bloom (2009); Bloom (2014)). The next section reviews the relevant literature, but several papers have provided compelling evidence that uncertainty was detrimental to economic activity during both the 2008 global financial crisis and the recent global pandemic. As with population aging, the degree of economic uncertainty has varied across states. Moreover, both motivating factors - the age distribution and aggregate uncertainty - have (separately) been linked to business cycle fluctuations.

A natural next step is to examine whether there is an inter-relationship between uncertainty and the age distribution. The analysis that follows shows that there is such a relationship, particularly for employment volatility. This interaction is important for understanding how both the aging population and changes in uncertainty affect fluctuations in the economy.

To estimate how the interaction between uncertainty and age distribution impacts employment volatility, this study analyzes quarterly data from 2000Q1 to 2017Q4 across US states. Utilizing instrumented regressions (IV) and instrumental local projections (LP-IV), the empirical specifications consider the effect of the age distribution, economic uncertainty, and their interaction term on employment volatility; the coefficients on uncertainty and the interaction term are the primary regressors of interest.

Unlike employment levels, which provide a snapshot of the workforce at a specific point in time, volatility captures the differences between periods, magnitude, and frequency of employment level changes. In this paper, employment volatility is measured using the standard deviation of employment within rolling windows of quarterly observations. Separate regressions on employment volatility are conducted for prime-aged and older workers. The baseline regression integrates both prime and young age groups, omitting the older working age group for reference. The baseline model uses the state-level economic policy uncertainty measure established by Baker, Davis, and Levy (2022). For robustness, alternative economic uncertainty measures, commonly used in the literature, are also considered.

There exits the possibility of endogeneity between the age distribution, economic uncertainty, and labor-market volatility. For example, migration is a potential omitted variable, which could affect both the age structure and labor-market dynamics. Additionally, state labor-market volatility could influence state uncertainty trends, not vice versa. To address endogeneity concerns, past birth rates instrument for the current working-age population, assuming their independence from current labor-market dynamics. Additionally, changes in national-level economic-policy uncertainty (ΔEPU) serve as an instrument for state-level changes ($\Delta SEPU$). The assumption is that national economic uncertainty influences local employment volatility by changing that state's 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 encounter reduced employment volatility; for each percentage point increase in the prime-aged working population's share, a one-percentage-point increase in $\Delta SEPU$ corresponds to a 1.4% increase in volatility, which accounts for a 55% reduction.

Further analysis decomposes the effects of uncertainty on employment volatility into volatility of job gains versus job losses and volatility of unemployment versus labor-force participation. The results indicate that states with a greater proportion of prime-aged workers experience a greater reduction in volatility of job losses compared to job gains, and a greater reduction in volatility of unemployment as opposed to labor-force participation. Additional analysis with different model specifications and outcome specifications, and when accounting for state controls including demographics, education, income, welfare policies, and political climate show robustness.

A series of local projection-IV (LP-IV) regressions show that employment volatility peaks four quarter after an increase in uncertainty. Specifically, an 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 far less employment volatility. More specifically, when contrasting states with a higher share of prime-aged workers to those with a higher share of older working age, the volatility is less evident: A one-percentage-point increase in $\Delta SEPU$ associates with only a 1.8% rise in volatility, marking a 70% reduction. This demographic effect is persistent through an eight quarter horizon.

The remainder of the paper is structured as follows: Section 2 reviews the literature. 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 different regression formats and incorporates various controls. Section 6 reports the dynamic findings using the LP-IV method. 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 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

[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).

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 benefits from Gupta et al. (2018), in which localized policy approaches are recommended, and Maestas, Mullen, and Powell (2023), which emphasized the advantages of state-based research designs. This paper contributes to both strands of research by considering the interactions between uncertainty and age demographics.

3 Data, Variables, and Identification

This section introduces the main variables and data sources, and addresses identification concerns. It first describes the computation of the outcome variable, employment volatility, and then describes alternative measures of economic uncertainty. The description of different age groups and their respective identification follows, concluding with a presentation of the summary statistics.

3.1 Determining the Outcome Variable: Employment Volatility

Employment data is sourced from the Bureau of Labor Statistics (BLS) Quarterly Census of Employment and Wages (QCEW). Employment volatility is constructed using standard deviations within a centered rolling window, capturing the cyclical employment fluctuations spanning the period from 2000Q1 to 2017Q4. The process involves several steps: Initially, monthly employment levels from 1998Q1 to 2019Q4 (before the onset of the Covid-19 pandemic) are collected.[2] Quarterly employment figures are calculated by averaging these monthly data points. The Hodrick-Prescott (HP) filter, with a smoothing parameter of 1,600, is then applied to the quarterly employment data. This method differentiates the overall economic trend from business-cycle deviations; the latter is defined as the cyclical employment level.[3]

As illustrated by Equation 1,the cyclical volatility for a specific quarter t is determined by computing the standard deviation of cyclical employment over a 17-quarter window centered on that quarter.[4] This 17-quarter period spans 4 years, with an additional quarter at its center. To investigate whether the results are robust to changing the definition of employment volatility, alternative rolling windows are employed in the robustness checks. [5]

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

Figure 3 illustrates the evolution of cyclical employment volatility across states by focusing on three quarters: 2001Q4, 2008Q4, and 2017Q4. [6] Overall, volatility was highest in 2008Q4 during the Great

[2]It should be noted that the original employment level data extends beyond the final sample by 8 quarters at both ends. The regression sample is narrowed to 2000Q1 to 2017Q4, excluding the first and last 8 quarters due to a lack of observations within the centered 17-quarter window.

[3]A smoothing parameter of 1,600 is typically used for quarterly data. As an example, Jaimovich and Siu (2009) use the HP filter with a smoothing parameter of 1,600 as their standard approach to measure cyclical volatility in response to business cycle changes at a specific time.

[4]The approach to constructing volatility for economic indicators such as employment varies in the literature. For example, Jaimovich and Siu (2009) use a 10-year rolling window for HP-filtered output volatility. Both Jaimovich and Siu (2009) and Lugauer and Redmond (2012) determine GDP volatility using a nine-year rolling window for 51 countries from 1950 to 2007. The use of a centered rolling window in this study aligns with research by Jaimovich and Siu (2009) and Heer, Rohrbacher, and Scharrer (2017), and the selected duration aims to reflect time periods referenced in prior studies.

[5]For the robustness checks, volatility is calculated over different quarter lengths (5, 9, and 13) using a centered rolling window. I also evaluate robustness to using a both backward and forward 17-quarter rolling windows. The forward window method considers employment figures from the current quarter and the subsequent 16 quarters.

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

Recession, followed by 2001Q4, and was significantly lower in 2017Q4 when many states experienced an economic boom. States in the northeast and southwest coastal areas exhibit higher volatility, while mountain states like Montana and Wyoming consistently show lower volatility, possibly due to their industry composition and workforce characteristics. For instance, Montana's economy leans heavily on agriculture and mining, with a predominately native-born workforce with education rates below the national average. In contrast, California, with 23% of the national foreign-born population, is dominated by industries like technology and tourism.

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, constructed using the equation below, is the percentage change in the State Economic Policy Uncertainty (SEPU) index:

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

The SEPU index is from Baker, Davis, and Levy (2022). To construct this index, the authors conduct an analysis of local news articles, discounting state-specific national papers. It comprises two facets: one highlighting local policy-driven uncertainty and another addressing 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 ensure comparability, the index is normalized using pre-2018 data on national policy uncertainty's average state-level impact. This approach distinguishes between state-specific and national policy uncertainties, with the *SEPU* indices subsequently validated against established economic benchmarks to evaluate their influence on economic activities such as employment and growth.

Figure 4 illustrates the evolution of $\Delta SEPU$ by focusing on the same three quarters used to take a snapshot of the state-level variation in employment volatility (2001Q4, 2008Q4, and 2017Q4). The figure begins at 2001Q1 due to missing $\Delta SEPU$ data in prior years for a few states. [7] These periods are also chosen based on key economic events that took place on those dates. During the 2001 recession,[8] states with large manufacturing and computer sectors like Michigan and Utah saw increased uncertainty, as depicted in dark blue. Additionally, elevated volatility is also observed in North Dakota, a state where the crude oil sector was a key driver of employment. The middle image reveals widespread uncertainty with darker tones during the Great Recession, particularly in financial hubs like Maryland, New Hampshire, Illinois, and Washington. By 2017Q4, post-Great Recession, reduced uncertainty evident in lighter tones in the right image is possibly associated with economic recovery.

3.2.2 Economic Policy Uncertainty

The state uncertainty measure may be endogenous to employment volatility if local newspaper search terms are influenced by local employment volatility – meaning the uncertainty measure is driven by volatility, not vice versa. Meanwhile, unobserved variables, such as state employment policies, state tax regulations, and state gross product, could also affect both uncertainty and volatility. To address this endogeneity, I use the change in national economic policy uncertainty measure, ΔEPU from Baker, Bloom, and Davis (2016) as an instrumental variable for state $\Delta SEPU$. The fundamental assumption is that a state's high uncertainty is not solely due to its own employment volatility, and U.S. uncertainty is not due to one state's volatility exceeding others'. Given that ΔEPU captures national economic uncertainty influenced by global political events rather than local factors, this method captures how national Economic Policy Uncertainty impacts state employment volatility by influencing state-level $\Delta SEPU$. A similar instrumental variable approach is employed in Basso and Rachedi (2021), where national military spending is used as an instrument for state military procurement to estimate the impact of age heterogeneity on state gross product growth.

The gree line in Figure 5 Panel A represents the EPU index; it peaks during economic downturns like

[7] Starting from 2001Q4, $\Delta SEPU$ data are available for more states.

[8] According to Langdon, McMenamin, and Krolik (2002) and the other literature, the longest postwar economic expansion in the U.S. concluded in 2001, when the economy entered a recession in March. Manufacturing's downturn began in the late summer of 2000 and intensified in 2001, with businesses significantly cutting back on spending for machinery, computers, and other capital goods.

the early 2000s recession and the Great Recession (highlighted in grey). Spikes appear during significant political and economic events, such as the 2010Q3 tax-cut expiration debate and the 2011Q3 debt-ceiling dispute. The blue line represents the growth rate, ΔEPU, with an average value of 1.78 (checked in red), capturing changes in the EPU index.

3.2.3 Other Uncertainty Measures

To further assess the robustness of the estimates, the analysis is repeated using alternative measures of economic uncertainty commonly-used in the literature. These indices include the percentage change in news-related policy uncertainty (ΔNPU) based on the indices developed by Baker, Bloom, and Davis (2016); the Global Economic Policy Uncertainty Index ($\Delta GEPU$) from Davis (2016); and the financial market volatility index (ΔVIX) obtained from the Federal Reserve Bank of St. Louis and referenced in Bloom (2009). Additionally, this paper considers the change in the proxy-Baa Corporate Bond Yield (expressed as ΔBAA) obtained 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 as may reflect consumers' perceived uncertainty about the future and has been employed by Leduc and Liu (2016). This study uses the negative of UMCS as an alternative proxy for consumer uncertainty. [9]

Figure 5 Panel B plots the co-movement among ΔEPU and five other national-level measures. These measures exhibit similar cyclical patterns. Financial indices (ΔVIX and ΔBAA) peak during the financial crisis in 2008, while news and political policy-related measures peak during significant policy events. Table A.1 in the Appendix displays the variance-covariance matrix for these measures spanning from 2000Q1 to 2017Q4. All measures exhibit strong positive correlations with each other, with values ranging from 0.287 (between $\Delta SEPU$ and ΔBAA) to 0.946 (between ΔEPU and ΔNPU). The following regression results focus on $\Delta SEPU$. Results for other measures can be found in the Appendix.

[9] Other details regarding the construction and sources of these uncertainty indices are documented in the Appendix.

3.3 Constructing Population Shares

3.3.1 Defining Age Groups

Population data is sourced from the US Census Bureau's National Population Estimate Program. This program provides resident population estimates by state for all age groups since 2000. The working-age population is defined as individuals aged 15 to 64 years, and is divided into three groups: young (ages 15-24), prime (ages 25-54), and old (ages 55-64). To compute quarterly measures, yearly proportions are linearly interpolated into quarterly values; considering the relatively slow evolution of age distributions, this interpolation is likely to produce an accurate estimate of the true age-group sizes. This study also presents robustness tests based on yearly data [10].

3.3.2 Applying Lagged birth rates to Address Endogeneity

State age structure might be endogenous to employment volatility if the working-age populations of states respond to economic uncertainty through migration flows. To address this possibility, this paper employs an instrumental variable (IV) method widely used in prior literature; that is, I use past state birth rates as instruments for the current working-age population (Shimer (2001), Lugauer (2012), Basso and Rachedi (2021), etc.). Using lagged peer birth rates as instruments can be a valid approach for several reasons. First, lagged peer birth rates are strongly correlated with the current age structure.[11] Second, lagged peer birth rates are exogenous to current economic factors and are unlikely to be influenced by state-level factors affecting current employment volatility. Third, after controlling for age share and state fixed effects, lagged peer birth rates are expected to have no direct impact on employment volatility.

Birth data from 1936 to 2002 were obtained from various editions of the National Center for Health Statistics Vital Statistics PDF files. Birth rates per thousand residents were adjusted for under-registration

[10] It is worth noting that the categorization of age groups varies in the literature. Definitions of age groups vary across studies: the BLS and Berg et al. (2021) define prime-aged individuals as those aged 25 to 54; Lugauer (2012) characterize prime-aged as those aged 20-54, with individuals under 35 labeled as young; Basso and Rachedi (2021) classify those between 20 and 29 as young; Jaimovich and Siu (2009) and Lugauer and Redmond (2012) categorize prime age as spanning 30-59; Jaimovich, Pruitt, and Siu (2013) consider individuals aged 15-29 as young and 30-64 as prime-aged; and Leahy and Thapar (2019) define the prime-aged range as 20-35. This paper follows the BLS and previous literature in the definition of prime.

[11] This correlation arises from common demographic factors influencing birth rates and age distribution across states. This argument is further supported by the first-stage regression results in Table 2.

whenever estimations were available.[12] Due to the unavailability of birth rates data for Alaska and Hawaii before 1956, these states are omitted (following Shimer (2001); Lugauer (2012); Basso and Rachedi (2021)); the panel therefore comprises 48 states along with the District of Columbia. These birth rates serve as instrumental variables for the working-age group (15-64 years) during the years 2000 to 2017.

To create lagged birth rates for various age groups, this study applies a rolling average of corresponding state birth rates. For example, to instrument the 25-54 age cohort in 2000, the average birth rates from 1946 to 1975 were used. Similarly, for 2001, rates from 1947 to 1976 were used. This method was consistently applied across all age groups from 2000 to 2017. For validation, the birth rates data for the 20-29 age group was cross-checked with rates from Basso and Rachedi (2021) for the years 2000 to 2015, resulting in a correlation of 99.6% (as displayed in Table A.3). This study contributes to the literature by extending the time-frame to cover the years 1936-2002, providing a more comprehensive examination of age heterogeneity.

3.4 Summary Statistics

Table 1 provides summary statistics for the main variables spanning from 2000Q1 to 2017Q4. The dataset contains 3,416 observations, with 112 missing observations for specific states during the early period from 2000Q1 to 2006Q1. The primary variable of interest, business cycle volatility of employment, exhibits values ranging from 517 to slightly over 318,000, with an average of 26,000. This variable is calculated from the standard deviation of cyclical employment levels, which itself ranges from -420,000 to 381,000 of cyclical population. The cyclical employment level is calculated by removing the general employment trend, which spans from 250,000 to 18,000,000 population, isolating the business cycle component.

The variable $\Delta SEPU$ measures changes in state economic policy-related uncertainty, expressed in percentage points, with values spanning from -92 to 616 and an average of 9. Each standard deviation change in $\Delta SEPU$ corresponds to a 51 percentage-point shift. This study also considers other economic

[12] Birth rates recorded before 1962 have two versions: one adjusted for under-registration and the other based on registered births. For the period from 1936 to 1962, this study utilizes the adjusted data, while data from 1963 onward is based on registered births.

indicators, and their summary statistics are provided in the Appendix. While direct comparisons of their values may not be appropriate, their counter-cyclical nature is consistent after inverting the cyclical *UMCS* series. Consequently, these variables are expected to share the same coefficient sign when used in regressions. The primary explanatory variables are the age groups young, prime, and old, with shares ranging from 17% to 30%, 54% to 68%, and 9% to 24%, respectively. To avoid perfect multicollinearity, this paper incorporates either one or two age groups in the regressions. The lagged birth rates for the young, prime, and old age groups range from 11 to 26 ‰, 14 to 28 ‰, and 16 to 35 ‰, respectively.

4 Estimating the Role of Age in Uncertainty's Effect on Volatility

This section investigates the relationship between ΔEPU and employment volatility, introducing age as a determinant and analyzing demographic impacts. It first presents the two-stage estimation specification. And then present the first stage regression results to validate the IVs, followed by the main estimats within an IV framework. The final part decomposes the effects on employment volatility using two approaches and evaluates the contributions of each factor to the influence of prime age on the employment volatility due to uncertainty.

4.1 Specification

To estimate the role of demographics on uncertainty-driven employment volatility, the following two stage regressions are employed:

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

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

The first three equations provide the specification for the first-stage regression. 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, $D_{i,t}$, aged k in state i at time t. The coefficient α_1 captures the influence of these lagged birth rates, indicating the IV effect at the average ΔEPU level. Equation 4 uses N_t to denote the national ΔEPU at time t, serving as an instrument for $\Delta SEPU$ in state i at the same time, labeled $U_{i,t}$, with the relationship given by the coefficient ρ_1. Equation 5 describes the interaction between the deviations of $D_{i,t}$ and $U_{i,t}$ from their means, using the interaction of the deviations of $B_{i,t-k}$ and N_t from their averages across time and states. In each equation, γ_i accounts for state-specific effects, and other terms serve as controls consistent with the second stage's structure.

In Equation 6, $Y_{i,t}$ 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 at time t.[13] γ_i denotes the state fixed effect. As N_t varies over time but not across states, these equations do not include time fixed effects. The term $D_{i,t} - \overline{D}$ reflects a state's age structure relative to its sample average, where $D_{i,t}$ measures the share of various age groups among the working population in state i at time t.[14] This age structure is instrumented with corresponding lagged birth rates relative to their average, $B_{i,t-k} - \overline{B}$. $U_{i,t} - \overline{U}$ represents the deviation of $\Delta SEPU$ from its average. This deviation is instrumented by the difference between the national ΔEPU and its mean, $N_t - \overline{N}$. The variable $\overline{U}$ represents the average value of $\Delta SEPU$ throughout the sample period. These additional national uncertainty measures from various sources, including $\Delta GEPU$, ΔNPU, ΔVIX, ΔBAA, and $UMCS$, are included as robustness checks, with the results reported in the Appendix.

The regression in Equation 6 aims to uncover the role of prime- and old-aged shares in the relationship between uncertainty and volatility. The coefficient β_1 captures the direct effect of $\Delta SEPU$ on volatility,

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

[14] Here, $\overline{D}$ is the sample's average value of either the prime or old share, while $D_{i,t}$ indicates the value for a particular state i at time t.

while β_2 represents the interaction between the demeaned $\Delta SEPU$ and the demeaned share of the working-age population. β_3 corresponds to the coefficient on the demographic effect alone. Specifically, β_1 quantifies the impact of $U_{i,t}$ on $Y_{i,t}$ when a state's age share ($D_{i,t}$) equals the sample average ($\overline{D}$). In this case, the influence of $U_{i,t}$ on employment volatility is solely represented by the coefficient β_1, voiding the β_2 term. If a state's age share deviates from the national average, β_2 accounts for each percentage-point difference in the age-group share from the sample average. This interpretation suggests that the effect of $U_{i,t}$ on volatility depends on a state's age structure. Taking deviations from the average allows for easier interpretation of the results.[15] By incorporating $D_{i,t}$ separately from its interaction with $\Delta SEPU$, β_3 accounts for age structure's direct influence on volatility, although this is not the primary focus of analysis.

The panel structure is crucial for uncovering demographic-dependent fluctuations in cyclical volatility driven by uncertainty. State fixed effects are employed to capture time-invariant state-specific factors, including geographic and historical attributes. Simultaneously, the model includes a time-varying and state-invariant variable N_t to control for unobserved time-varying characteristics common to all states, such as global economic trends and common policy changes. Identifying the causal relationship depends on both state- and time-varying factors. For example, the age distribution of the working-age population varies among states at any given moment: in 2000Q1, New Hampshire's prime age accounted for 68%, while in Utah, it was only 59%. Furthermore, states' relative ranks change over time: New York, which had the 38th-lowest prime share in 2004, climbed to the ninth-highest by 2017.

4.2 Checking the Validity of the IVs

Table 2 presents the results of the first-stage regressions based on Equations 3, 4, and 5. In Equation 3, $D_{i,t}$ is segmented into three working-age groups: young, prime, and old. Columns 1-3 display the results for each group. Columns 4-6 represent the regression results following Equation 4 for corresponding working-age groups. The last columns display the first-stage regression results based on Equation 5.

The coefficients across all columns are significant. Specifically, coefficients on birth rates (first three

[15] 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 ($D_{i,t} = \overline{D}$).

columns) are consistently positive and significant at the 1% level, and the F-statistics are high. These results indicate a strong correlation between age groups and their respective lagged birth rates, confirming the validity of using lagged peer birth rates as an instrument. Notably, the F-statistics show a decreasing trend from young to old, aligning with expectations. As time progresses and populations age, influences such as migration and mortality introduce discrepancies between the state's demographic structures of older individuals and their corresponding lagged birth rates.

The coefficient for ΔEPU in the following three columns is positive and significant at the 1% level, suggesting a significant positive correlation between these variables. This supports the use of national ΔEPU as a valid instrument for $\Delta SEPU$. The last three columns report 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 the lagged young birth rates and ΔEPU shows a positive sign, while the following two columns are negative. Various reasons can explain these coefficients. One possibility could be that states with higher prime and old peer birth rates respond to economic uncerrtainty with more migration flows, leading to smaller shares of these age groups. However, their significance suggests that the interaction of ΔEPU and $B_{i,t-k}$ serves as a valid instrument for the interaction of $\Delta SEPU$ and $D_{i,t}$, confirming the validity of the identification for the main results.

4.3 Analyzing the Role of Age

Table 3 presents the main estimate results based on Equation 6. Newey-West autocorrelation-robust standard errors are used in all regressions to address potential heteroskedasticity and autocorrelation, allowing for one year of dependence[16]. Due to missing $\Delta SEPU$ data early in the sample, 3,416 observations are used instead of the possible 3,528.

Throughout the three columns, the dependent variable is the standard deviation of state-level cyclical employment, $Y_{i,t}$. Independent variables include the growth rate of state economic policy uncertainty, $\Delta SEPU$ ($U_{i,t}$); young (aged 16-24), prime (aged 25-54), or old (aged 55-64) among the total working-age (15-64) population, $D_{i,t}$; and the interaction term between the demeaned values $(D_{i,t} - \overline{D}) \cdot (U_{i,t} - \overline{U})$. The

[16] Refer to Newey and West (1987) and Newey and West (1994) for details.

results were obtained by instrumenting age shares with their respective lagged birth rates and $\Delta SEPU$ with national ΔEPU, while also including state fixed effects. Standard errors are reported using Newey-West with one lag. The checked coefficients are not the main interpretation of interest, and thus, they are not reported. Estimation results suggests that states with a greater prime-aged share are associated with reduced employment volatility following economic uncertainty.

First, considering Column 1, which reports the regression regresses the employment volatility on $\Delta SEPU$, $(Prime_{i,t} - \overline{Prime}) \cdot (U_{i,t} - \overline{U})$, and $Prime_{i,t}$. The estimate on $U_{i,t}$ indicates that states with an average prime-aged share will experience an increase in employment volatility for every one-percentage-point increase in $\Delta SEPU$. Second, the estimate on the interaction term indicates that for each additional percentage point of prime-aged share, there is a significant reduction in volatility. This effect is both statistically and economically significant. Next, Column 2 reports the regression regresses the employment volatility on $\Delta SEPU$, $(Old_{i,t} - \overline{Old}) \cdot (U_{i,t} - \overline{U})$, and $Old_{i,t}$. The estimate on on $U_{i,t}$ suggests that states with an average old-aged share will see an increase following a one-unit increase in $\Delta SEPU$. Furthermore, the estimate on the interaction suggests that a higher share of old intensifies this correlation for each $\Delta SEPU$ unit, with an additional share of old associated with higher employment volatility. This effect is statistically and economically significant.

The baseline regression, reported in Column 3, incorporates both prime and young, along with their interactions with $\Delta SEPU$; the reference category is the old group and its interaction with ΔEPU. The estimate on $_{i,t}$ indicates that states with an average age distribution are estimated to experience an 86-unit increase in employment volatility for each one-percentage-point increase in $\Delta SEPU$. The estimate on the interaction term shows that states with a higher proportion of prime-aged individuals have lower uncertainty-induced volatility. Specifically, a one-percentage-point increase in the prime-aged share (relative to the sample average) associates with reduced volatility by 48 units compared to states with a larger old-aged share. This amounts to a 55% reduction per percentage point increase in economic policy uncertainty increase.[17] To make the interpretation units more economic meaningful, consider the

[17] The baseline regression with various national economic uncertainty measures is reported in the Appendix. Overall, consistent negative and significant signs are found on uncertainty coefficients, and consistent negative signs are found on the various interactions.

average of cyclical employment volatility is 26,921, and the average of $\Delta SEPU$ is 9.92. Given that the coefficient on $U_{i,t}$ is 86.94, the uncertainty elasticity of volatility is calculated to be 3.2% (given by $\frac{86.94\times 9.92}{26{,}921}$): a one-percentage-point increase in the $\Delta SEPU$ corresponds to a 3.2% increase in volatility for states with an average age structure. This uncertainty effect diminishes by 55% (determined by $\frac{-48.38}{86.94}$) leading to an elasticity of 1.4% (found using $\frac{(86.94-48.38)\times 9.92}{26{,}921}$). Hence, a one-percentage point rise in the $\Delta SEPU$ results in a 1.4% rise in volatility for states that have a one percentage point higher prime share than those with a one percentage point higher old share. This comparison unveils the primary empirical finding of this paper: states with a higher prime share exhibit both statistically and economically significant lower employment volatility associated with economic uncertainty impact.

4.4 Decomposing the Employment Volatility

The primary estimate from the previous section indicates that the prime-aged share is associated with reduced volatility following economic uncertainty. To provide further analysis of the effect on employment volatility, this section presents two decompositions. The first subsection investigates whether uncertainty-driven employment volatility arises more from fluctuations in individuals gaining employment (job gains volatility) or from those losing employment (job loss volatility). The next examines whether employment volatility comes more from job transitions within the labor force (unemployment volatility) or from fluctuations in people entering or exiting the labor market (participation volatility). The results suggest that all of these components contribute to the reduced uncertainty-related employment volatility in states with a higher prime-aged population, but that more significant contributions come from job-loss and unemployment volatility.

4.4.1 Contributions of Job Gains and Losses

Job gains represent positive employment changes over time, while job losses represent negative changes; the difference between job gains and losses equals the change in employment. To calculate the volatility of job gains and losses spanning from 2000Q1 to 2017Q4, I collect data for the period 1998Q1 to 2019Q4 from the Business Employment Dynamics (BED) statistics provided by the BLS. This complements the household survey data. The summary statistics can be found in Table A.4.

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

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

The volatility of net employment change over time is denoted as $Vol(Employ_{i,t} - Employ_{i,t-1})$. It can stem from the volatility in people gaining jobs ($Vol(Gain_{i,t})$) or losing jobs ($Vol(Loss_{i,t})$). For consistency with previous sections, I use cyclical employment volatility ($Y_{i,t}$) as a proxy for the left-hand side. By applying the HP filter to remove common economic trends from all employment levels, left with the cyclical component, and its volatility can be interpreted as the volatility of employment changes. Following this rationale, the volatility of job gains and losses is calculated as the standard deviation of the gain and loss levels after applying the HP filter[18] By estimating Equation 6 for each volatility component, the sum of coefficients should correspond to β_2 from regressing Equation 6. [19] Examining job gains and losses to decompose labor-market dynamics is not new. Since Davis and Haltiwanger (1992), many studies have used job gains and losses to study labor market dynamics. For example, Hairault, Langot, and Sopraseuth (2019) study the cyclical volatility of job-market transition rates across age demographics, revealing distinct volatility patterns among age groups.

Table 7 presents the decomposition estimates on volatility of job gains and losses. Columns 1-3 focus on the volatility of job gains, while columns 4-6 estimate the volatility of job losses, mirroring the first three columns in Table 2. Column 1 assesses the impact of the prime share on job-gain volatility; while the sign of the interaction coefficient aligns with previous findings, it lacks statistical significance. Column 2 shows a positive but statistically insignificant effect of old. While Column 3 identifies a significant comparative effect between prime and old: an additional percentage point of prime-aged share, compared to the national average, results in states experiencing less volatility than with an additional old share. This leads to a 39% reduction in the total impact of uncertainty on volatility. Specifically, a one-percentage-point increase in $\Delta SEPU$ changes its effect on employment volatility from 2.5% (calculated as $\frac{23\times 9.92}{9{,}067}$) to

[18]For simplicity, the covariance term between the volatility of job gains and job losses is omitted for now due to lack of information. However, this warrants future research attention.

[19]Hall and Jones (1999), Feyrer (2007), Maestas, Mullen, and Powell (2023), etc employ a similar strategy in their IV regressions. They decompose the output per capita as: $\text{GDP}_{st}/N_{st} = \text{GDP}_{st}/\text{Hours}_{st} \times \text{Hours}_{st}/L_{st} \times L_{st}/N_{st}$.

1.5% (calculated as $\frac{14 \times 9.92}{9{,}067}$). The exact values of volatility for job gains are provided in the tables appendix.

Columns 4-6 report the regression on the volatility of job loss. Column 4 indicates that a higher prime share significantly reduces job-loss volatility, whereas Column 5 shows no significant effect for old. Column 6 presents significant results when comparing prime and old shares: an additional percentage point in the prime share results in a 71% reduction in the $\Delta SEPU$ effect on job loss volatility. Specifically, comparing states with a one percentage point higher prime share to those with one percentage point higher old share changes the total uncertainty impact on job loss volatility from 2.1% (calculated as $\frac{21 \times 9.92}{10058}$) to 0.59% (calculated as $\frac{6 \times 9.92}{10058}$). These results are consistent with the primary findings on employment volatility. The prime effect contributes about 38% (calculated as $\frac{9}{24}$) to gain volatility and 62% (calculated as $\frac{15}{24}$) to loss volatility.

Further decomposition of the volatility of cyclical employment changes into the volatility of job gains and losses is detailed in Appendix Table A.5. This table offers a more detailed breakdown and is consistent with prior results. The sum of the coefficients on gains and losses surpasses that of the volatility of cyclical employment changes. Overall, these findings suggest that prime individuals experience reduced volatility in both job gains and losses, with a greater reduction observed in loss volatility.

4.4.2 Contributions of Changes in Labor Market Participation

Labor-market participants fall into two categories: employed and unemployed. Therefore, the volatility of cyclical employment can be attributed to 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 data is from BLS QCEW Statistics with the summary statistics are reported in Table A.4.

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

So that,

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

The same as employment data, both unemployment levels and labor-force participation rates are assessed in cyclical terms. The volatility of unemployment and participation is calculated from the standard deviations of their respective cyclical measures. Data on unemployment and labor-force participation across states from 1998Q1 to 2019Q4 are obtained from the BLS QCEW. Following the previously established approach and ignore the covariance for now, the sum of coefficients on the volatility of employment and participation should equal the volatility of employment, as shown in Equation 10. Table 8 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, displaying the effects of prime, old, and their comparative impacts.

The findings is consistent with the main results in this paper: states with a higher share of prime-aged individuals typically experience reduced volatility, while states with a higher share of old-aged individuals show the opposite trend. Specifically, as illustrated in columns 1 and 3, states with greater prime-aged shares exhibit notably less volatility, while Columns 3 and 6 show a significant difference between the effect of prime and that of old. The coefficients indicate that a one-percentage-point increase in the prime share reduces the direct impact of $\Delta SEPU$ on unemployment volatility by 49%, from 84 to 43 units. It also decreases the impact of $\Delta SEPU$ on participation volatility by 88%, from 14 units to 1 unit.

The influence of the prime age group on uncertainty-driven volatility, as revealed by previous findings in employment volatility, accounts for approximately 76% of the demographic impact on unemployment volatility. In contrast, labor-force participation comprises the remaining 24%. This suggests that higher prime-aged shares reduce employment volatility primarily by reducing the likelihood of transitioning between employed and unemployed statuses, rather than by entering or exiting the labor force.

Overall, this subsection 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 Robustness Analysis

This section presents a series of robustness analysis to check the primary findings that states with more prime age have a notably lower employment response to economic policy uncertainty.

5.1 Applying Reduced Form

Table 4 shows the results of reduced-form regressions, which confirms the main regression results. In the first three columns, ΔEPU is directly included as a covariate, rather than an instrument is denoted as partial reduced form. Column 1, mirroring the first column of Table 3, shows a direct effect of 101 for ΔEPU and a -40 for the prime interaction, both statistically significant. In Column 2, consistent with the second column of the main table, larger coefficients for ΔEPU and the old interaction are observed, with the latter not reaching statistical significance. Column 3, comparable to the baseline regression in the third column of the main table, suggests that an increased prime share results in a reduction of volatility by 75 units for each percentage point of uncertainty, which corresponds to a 55% decrease in total uncertainty impact.

Similar results are observed in the regression when regressing employment volatility on ΔEPU and lagged birth rates. Theses regressions using ΔEPU and lagged birth rates as independent variables are denoted as the reduced form. In Column 4, there is a negative coefficient of 15 for the prime interaction. Column 5 shows a positive but statistically insignificant coefficient for old, while Column 6 reveals a negative coefficient of 42 when comparing the effect of the prime share with that of the old share. The results above confirm the significant role of prime-aged share in mitigating uncertainty-driven volatility

5.2 Regressing With Controls

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

5.2.1 Specification

Variations in birth rates across states can arise from factors such as the baby boom after World War II, migration patterns, and economic growth. These factors can impact both birth rates and employment volatility. States with higher migration rates typically have a diverse labor market with a larger share of younger and highly educated migrant workers. States experiencing high economic growth often offer more job opportunities.

The above factors, which influence both the local population's age structure and local labor-market fluctuations, could introduce potential errors. Omitted heterogeneity across states could violate the identification restriction, especially if it is associated with local economic uncertainty and lagged birth rates across states over time (Basso and Rachedi (2021)). The subsequent regressions are employed to address this concern; the underlying assumption is that, by accounting for these potential confounding factors, the results strengthen the credibility of the IV approach. The following equation represents the second-stage regression, factoring in various 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 diverse controls encompassing state demographics, education, income types, welfare policies, and the state's political climate. The primary interpretation of interest is λ_2: it demonstrates how including different controls influences the prime age effect on employment volatility in the wake of economic uncertainty. λ_4 indicates how the controls themselves affect employment volatility following economic uncertainty. The age shares $D_{i,t}$ and national economic policy uncertainty $U_{i,t}$ are instrumented as in previous regressions. The subsequent regressions are conducted in line with the baseline regression, facilitating the comparison between states with a higher share of *prime* and states with an older working population. Summary statistics for all the control variables can be found in the Appendix. The following section discusses a selection of key controls and their respective results.

5.2.2 Controlling State Demographics

Numerous studies have incorporated demographic controls to investigate the relationship between demographics and labor-market outcomes. Jaimovich, Pruitt, and Siu (2013) employ education and gender as controls to demonstrate labor-market fluctuations across distinct age groups. Hoynes, Miller, and Schaller (2012) incorporates less-educated men and minorities to examine cyclic variations. Aaronson et al. (2014) includes age- and sex-specific determinants affecting labor participation. Furthermore, Mennuni (2019) identifies correlations between a predominant female workforce, higher education, and younger demographics with diminished business cycle volatility.

The subsequent regression integrates various demographic controls following Equation 20. The data from 2000-2017 is sourced from IPUMS-CPS. Following prior literature, this study involves the female marriage rate, white share, black share, immigrant rate, Hispanic share, number of hours worked in a week, and the share of low-skilled workers into the regression to account for the demographic effect in driving the impact of prime age share on uncertainty's effect on employment volatility.

The regression results are reported in Table 5. The first column reports the baseline regression for reference. Across the columns, the inclusion of variables such as the female marriage rate, immigrant rate, and Hispanic share is associated with a smaller magnitude for the coefficient on the prime-uncertainty interaction term. Holding these demographics at sample average level, the prime age demonstrates a somewhat smaller mitigating effect on the uncertainty's impact on employment volatility. The coefficient on λ_2 changes from -48 to -43, -15, and -28 respectively.

In contrast, the magnitude of the coefficient on λ_2 increased by including black share, working hours in a week, and low skill share. Holding the state's black share, working hours, and low-skilled share (obtained education lower than a high school diploma) at sample average, the prime age share demonstrates a higher mitigating effect on the uncertainty's impact on employment volatility compared to the baseline estimate. More specifically, the coefficient on the prime interaction term changed from -48 to -52, -64, and -55 respectively.

The coefficient on the control interacting with the uncertainty (reported in row 3 and forth) can be interpreted as the changes in uncertainty impact on volatility with a higher share of these controls. Except for a higher share of white (column 4), where the uncertainty impact on volatility is associated with a lower value, the other columns demonstrate a non-significant effect or positive effect. Particularly, states with higher working hours (Column 8) are associated with a higher uncertainty impact on volatility, almost doubling the effect for states with the sample average share of working hours. Overall, the main results hold when including various demographic controls.

5.2.3 Controlling State Income

This subsection examines the influence of state sectoral incomes on the analysis following Equation 20. The income variables include state total personal income, state total wage income, and sectoral incomes from construction, manufacturing, retail trade, transportation, and the health department. The data is from the Bureau of Economic Analysis (BEA) Regional Economic Accounts program, with quarterly variations calculated from monthly averages.[20] Lots of previous work have involved income level and industry contributions in economic activity analysis. For example, Bouakez, Guillard, and Roulleau-Pasdeloup (2020) identified sectoral heterogeneity as a factor influencing the effect of government spending. Guimaraes and Tiryaki (2020) emphasized the role of trade in age-driven output volatility with Hoynes, Miller, and Schaller (2012) also explored industry-specific cyclicality.

When controlling for all income measures, the magnitude of the coefficient on λ_2 becomes smaller. That is, when controlling for various income measures, states with a higher share of prime exhibit a smaller mitigation effect. The coefficient changes from -48 to -14 (by including health income) and to -39 (by including manufacturing income). Furthermore, the coefficients on the interaction between incomes and uncertainty are consistently positive and significant. This means that with a higher share of personal, wages, and sectoral incomes, states experience a greater uncertainty impact on employment volatility.[21]

[20] Ideally, quarterly state-level GDP data would be used, but available datasets are restricted to post-2005 data. As a substitute, state sectoral income serves as the most suitable alternative.

[21] The regression results, which include controls from various sources such as education levels, state average personal income levels, welfare policies, and political climate, are reported in the Appendix. In conclusion, the main results remain consistent and robust across the regressions with these controls.

6 Exploring Dynamic Responses of Employment Volatility

This section presents the dynamic empirical findings using the local projection-IV (LP-IV) method. Initially, the LP-IV specification is presented, and then the dynamic estimation results following LP-IV are discussed. Further analysis is conducted based on the earlier two decomposition approaches. The main finding indicates significant negative responses in employment volatility from t to $t+8$ to ΔEPU shocks for states with higher prime share, both in terms of magnitude and duration.[22]

6.1 Specification

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

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

Volatility is calculated as the standard deviation of a centered 9-quarter rolling window of cyclical employment.[23] 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

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

[23] where

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

and

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

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 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.[24] 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. [25] 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.

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

[25]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.

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 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 $\frac{(120)\times9.92}{26{,}921}$), 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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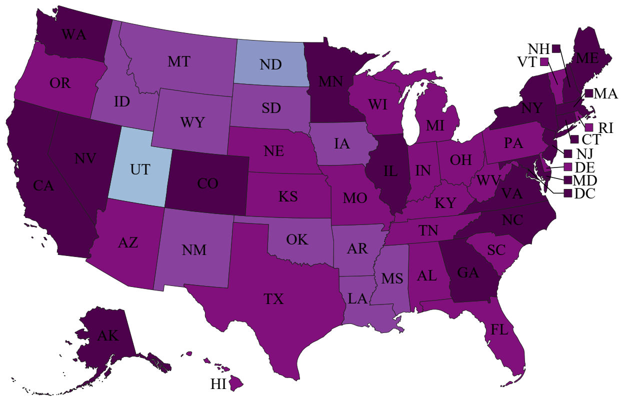
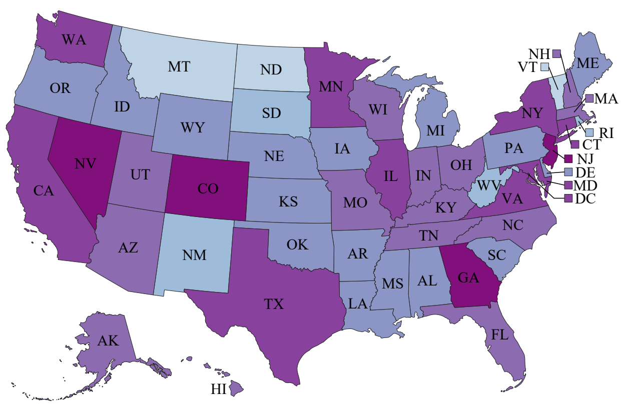
Figures

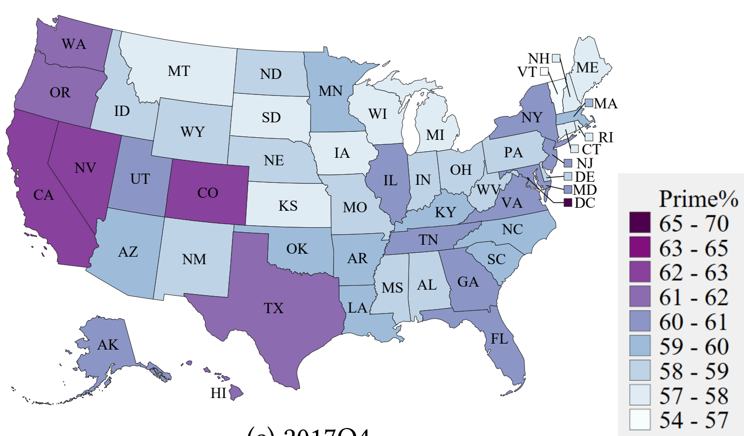
Figure 1: Evolution of prime Age Share



(a) 2001Q4



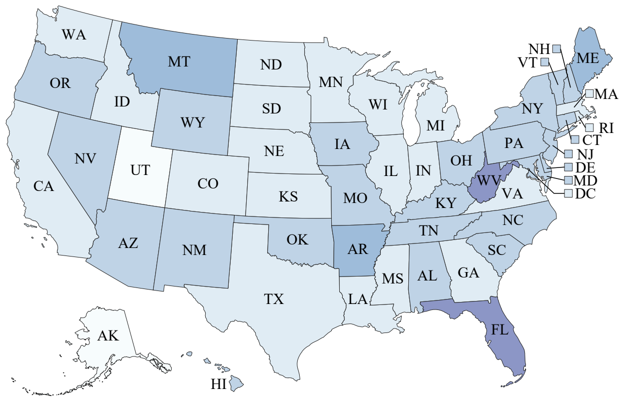
(b) 2008Q4



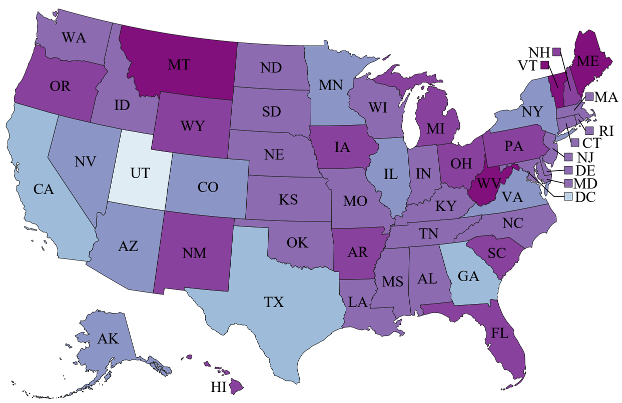
(c) 2017Q4

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.

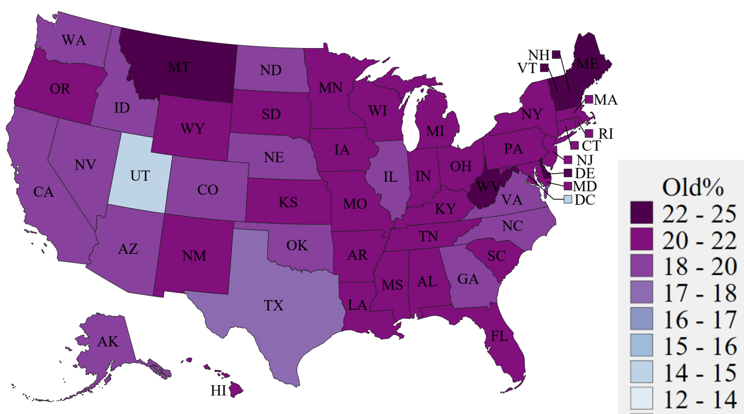
Figure 2: Evolution of old Age Share



(a) 2001Q4



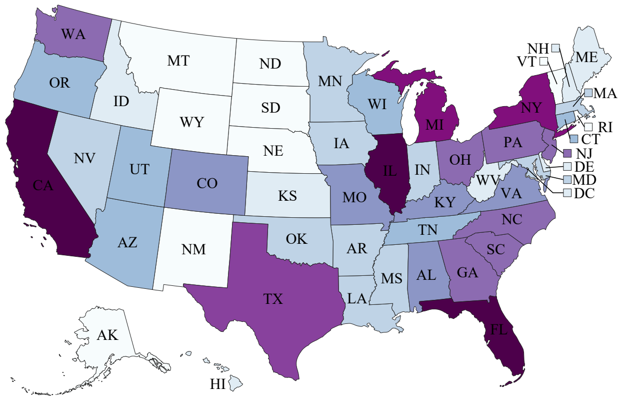
(b) 2008Q4



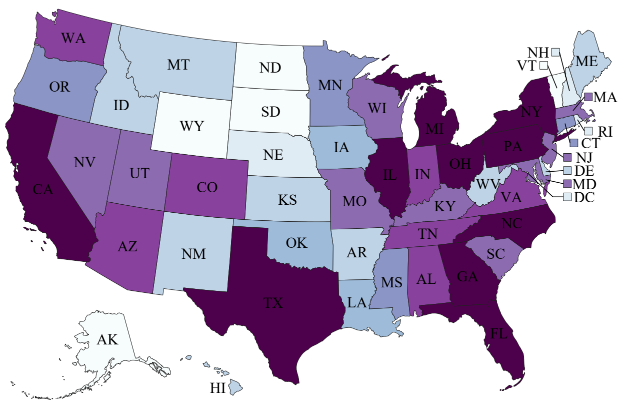
(c) 2017Q4

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.

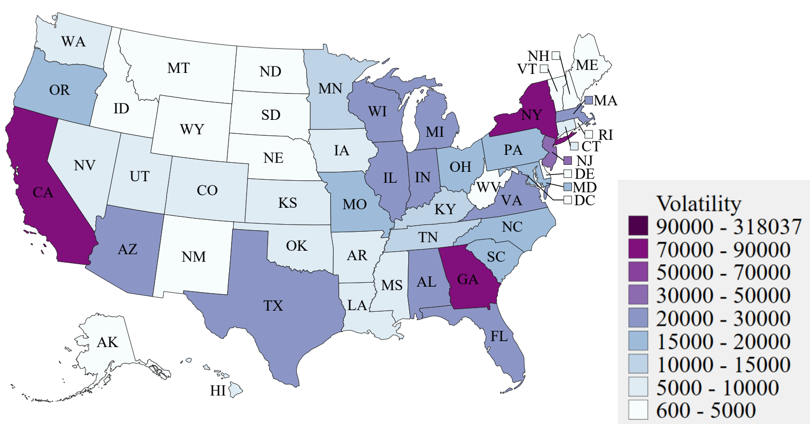
Figure 3: Evolution of Cyclical Employment Volatility



(a) 2001Q4



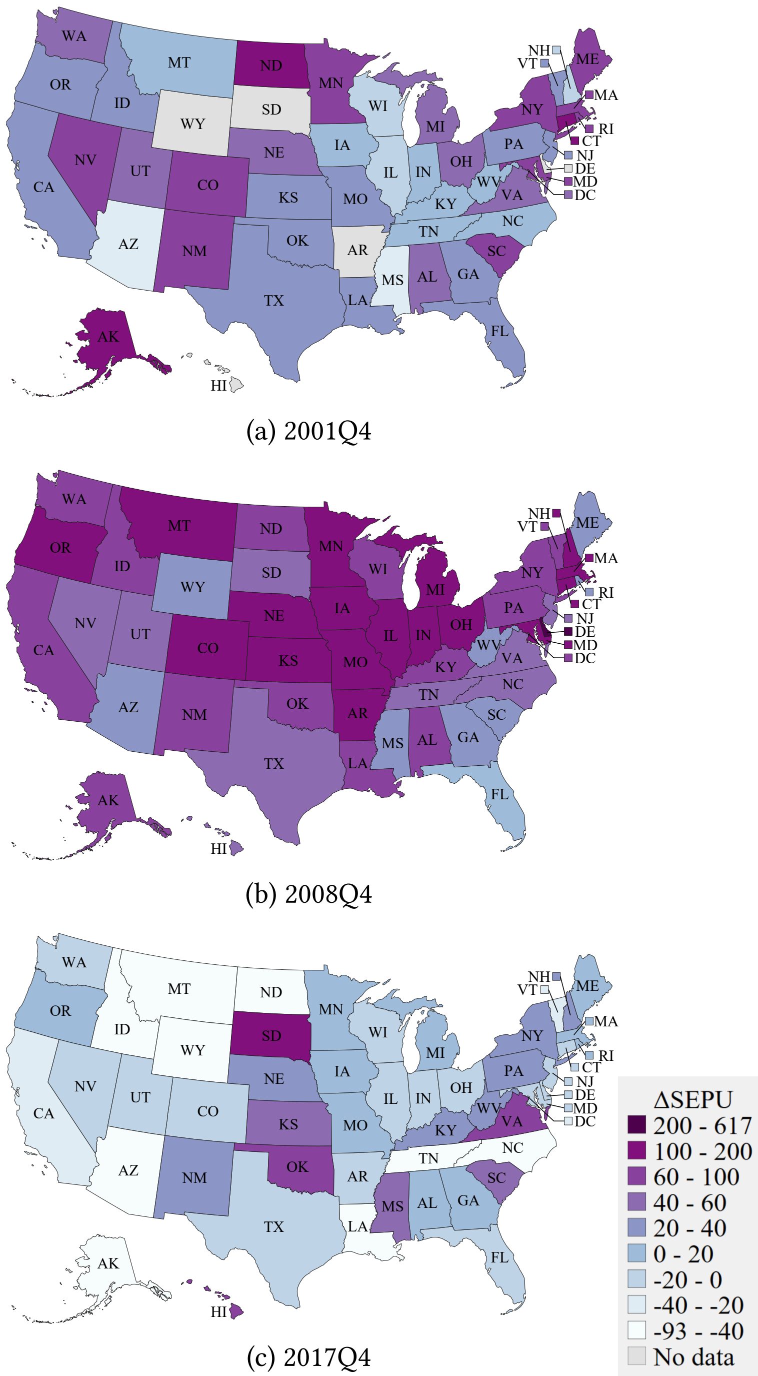
(b) 2008Q4



(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

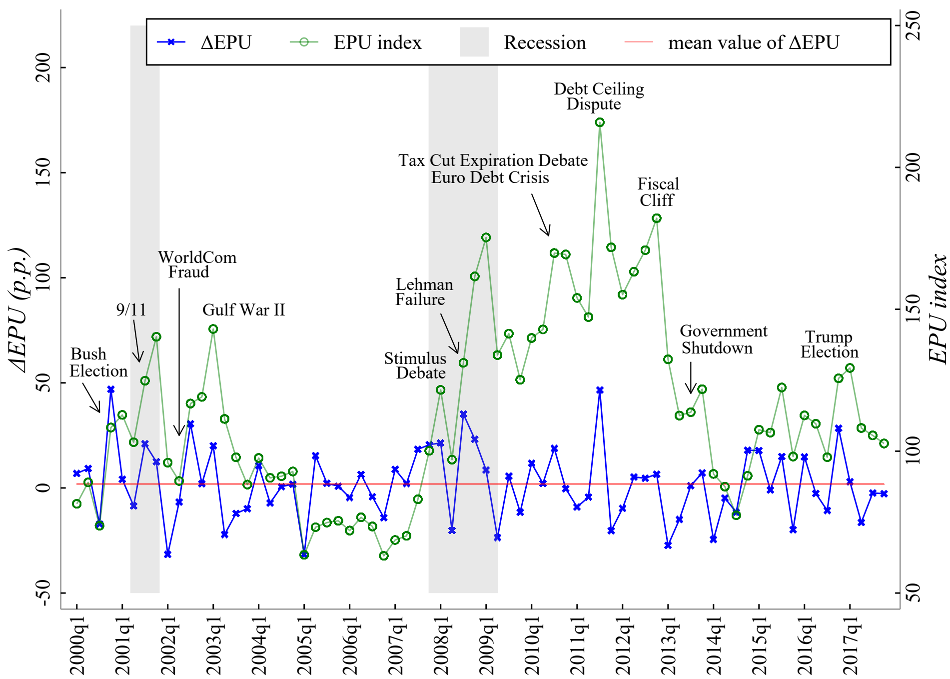
(b) 2008Q4

(c) 2017Q4

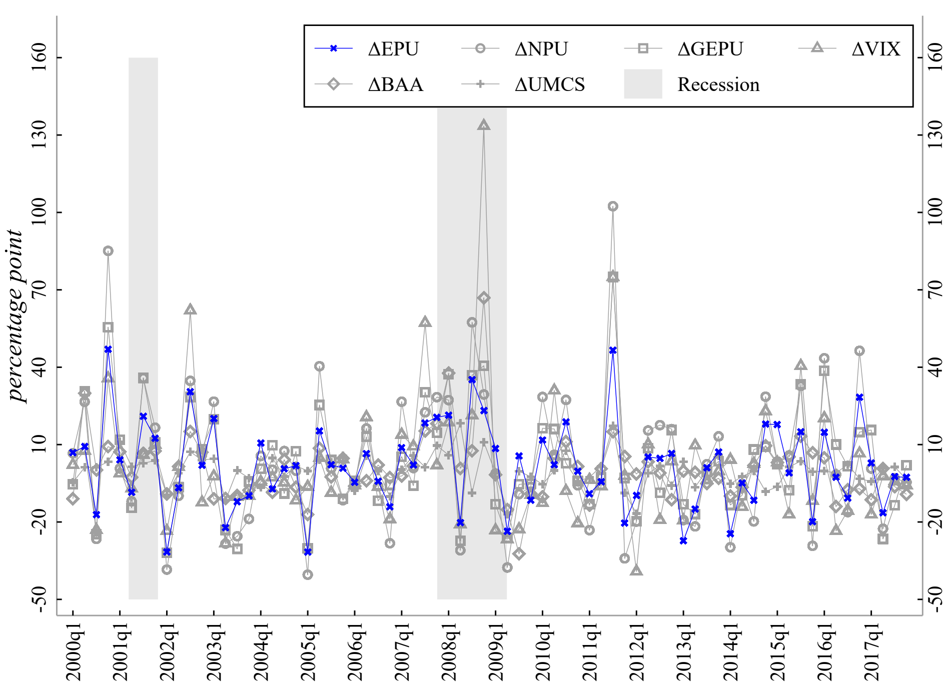
Note: The figures represents the state economic policy uncertainty ($\Delta SEPU$) measures for 2001Q4, 2008Q4, and 2017Q4. This variable is calculated as the percentage change in the state *EPU* index from Baker, Davis, and Levy (2022). During the Great Recession, the measure for 2008Q4 exhibits greater 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

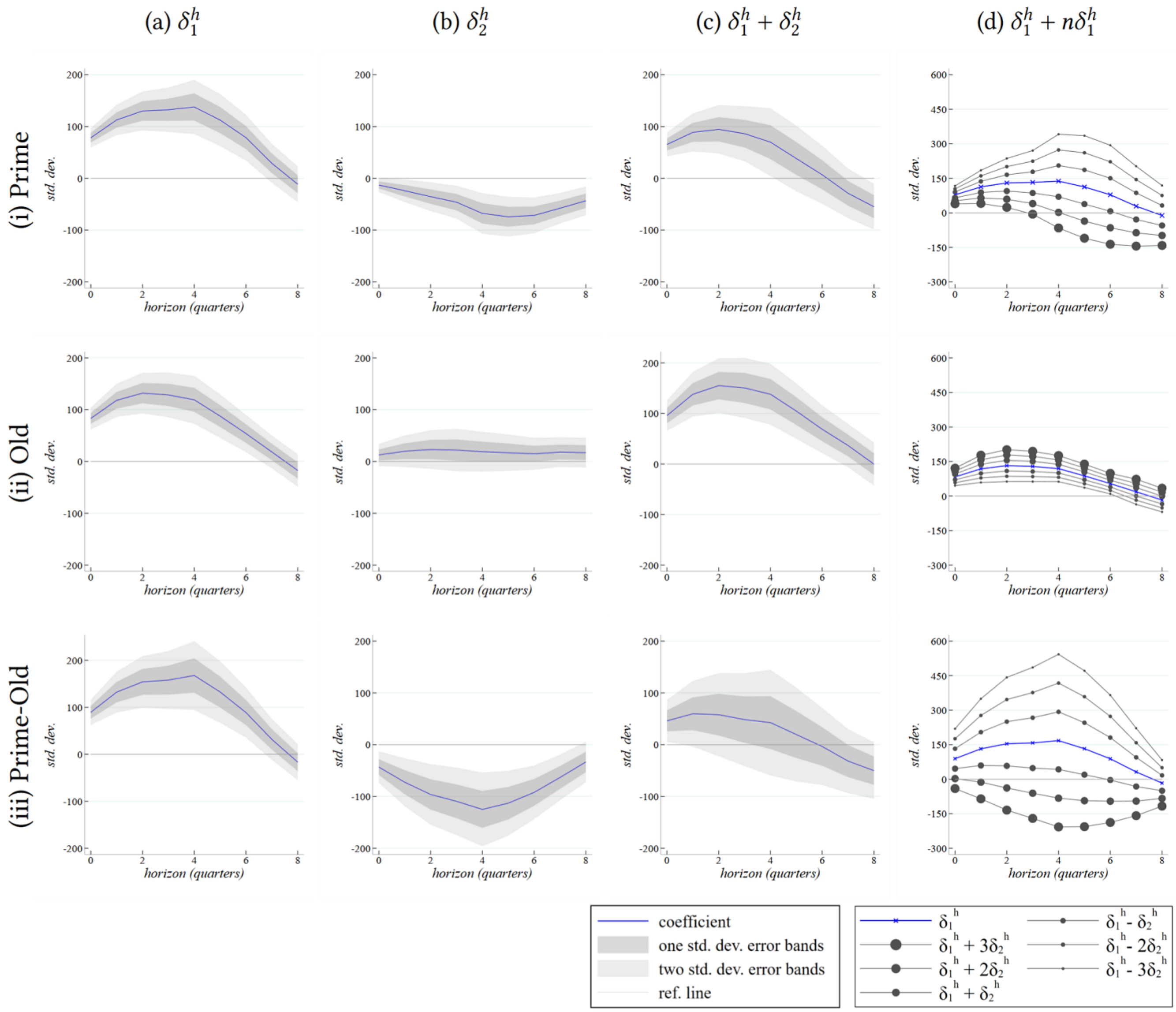


(b) Other Measures



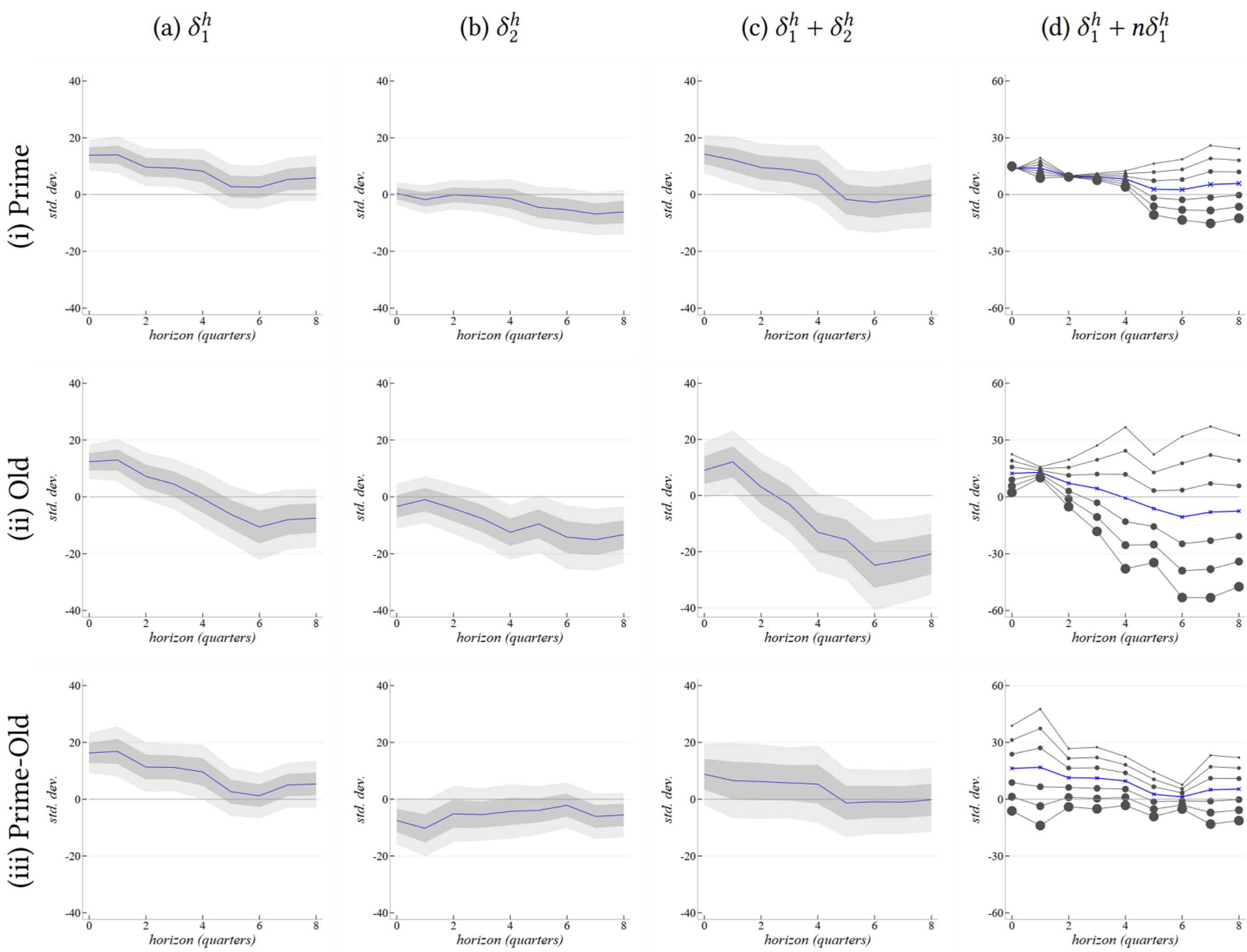
Note: *EPU* index in Panel A (illustrated in green) is proposed by Baker, Bloom, and Davis (2016), and the data are collected from the policy uncertainty website. The blue curve depicts the percentage changes of the index, referred to as ΔEPU in this paper. Panel B depicts five other national uncertainty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

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



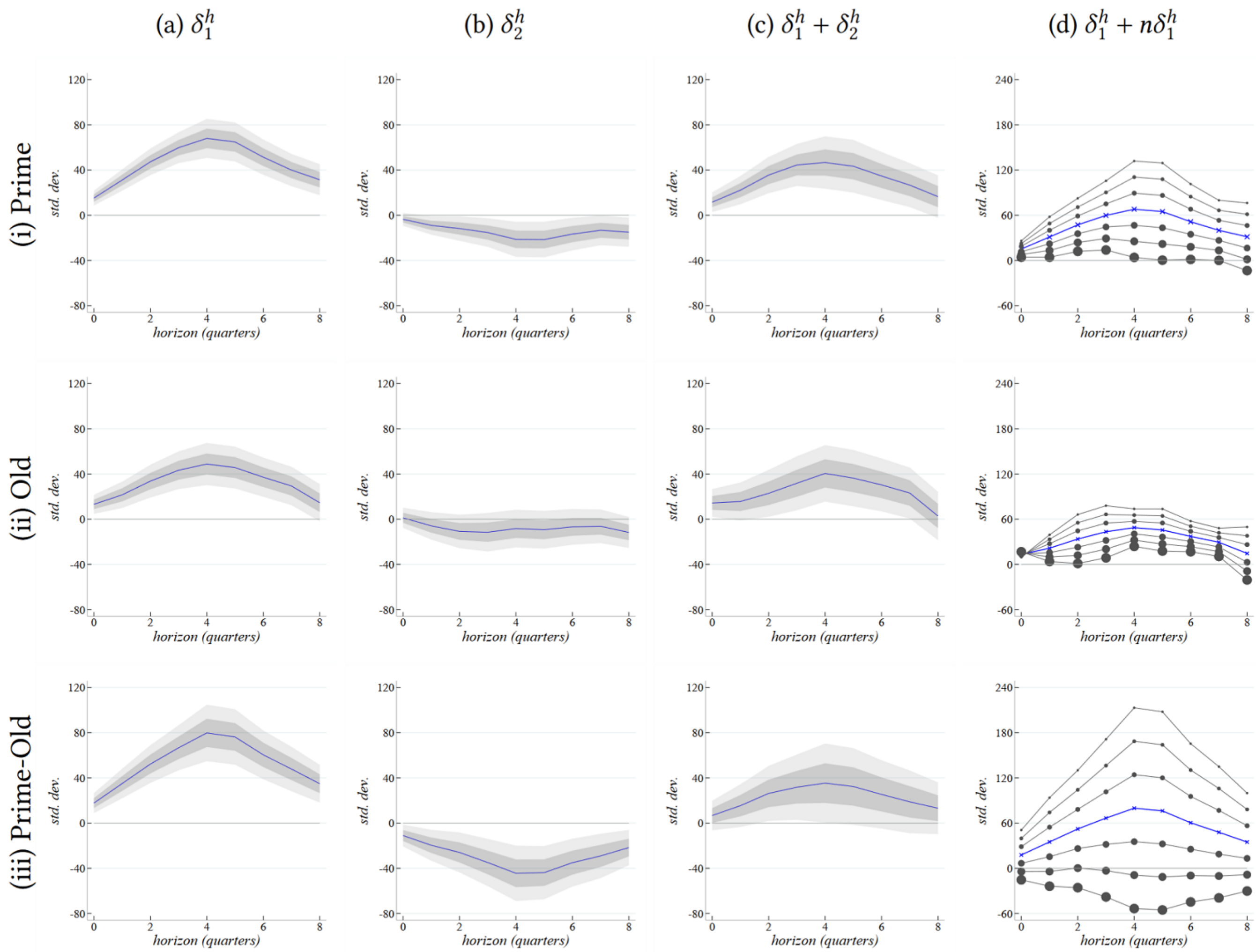
Note: The figures display the LP-IV Impulse Response Function (IRF) of cumulative cyclical employment volatility in response to various uncertainty measures among ages groups, as described by Equation 10. These figures elucidate the dynamic shifts in employment volatility due to a one percentage point 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



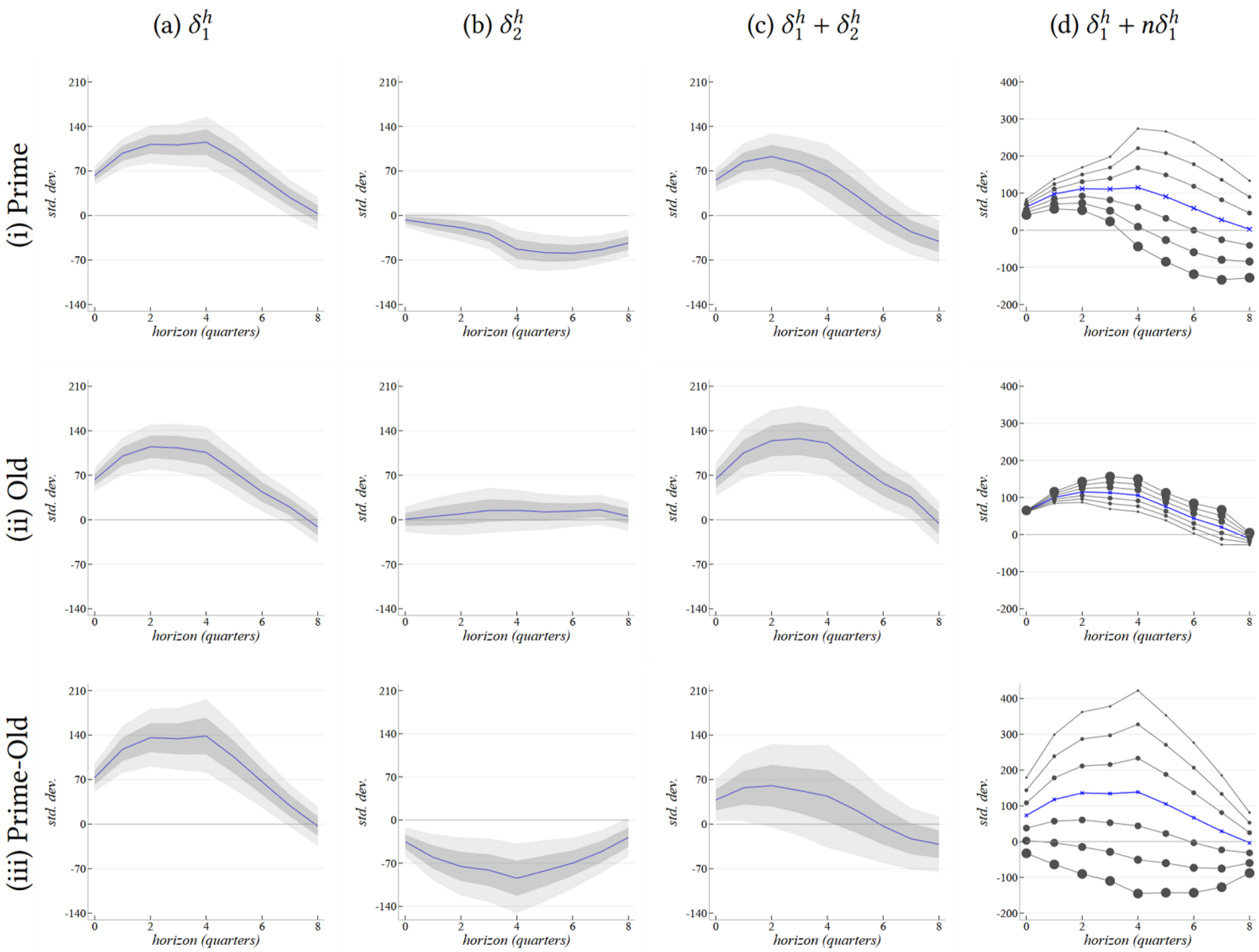
Note: The figures display the LP IRF of cumulative job gains volatility in response to various uncertainty measures and among age groups, as described by Equation 10, with the outcome variable switching to job gains volatility. These figures illustrate the dynamic responses in volatility due to a one 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



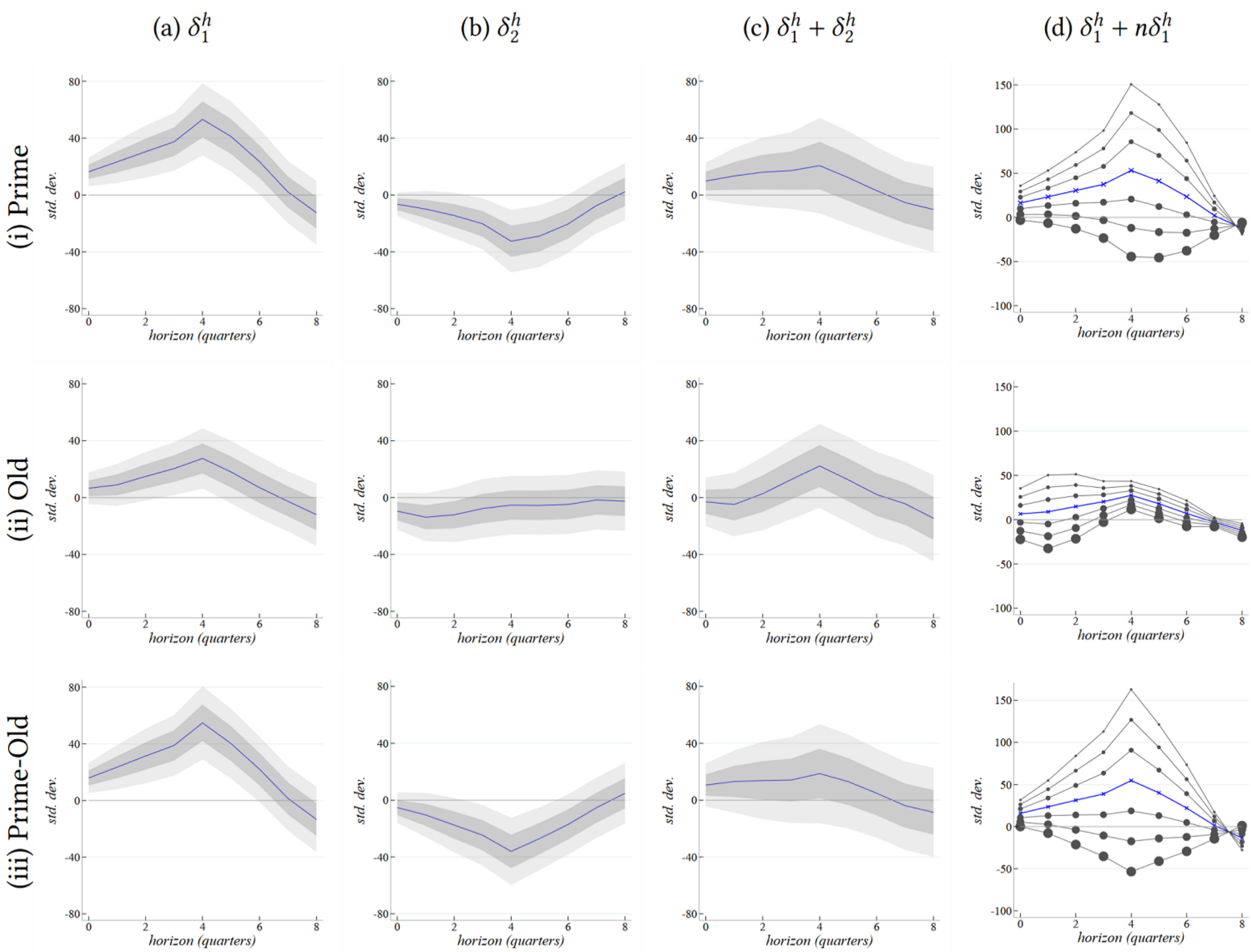
Note: The figures display the LP IRF of cumulative job loss volatility in response to various uncertainty measures and among age groups, as described by Equation 10, with the outcome variable switching to job loss volatility. These figures illustrate the dynamic responses in volatility due to a one percentage 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.

Tables

Table 1: Summary of Main Variables

	Mean	Min	Max	SD
Emp. Vol. ($Y_{i,t}$)	26,921	681	318,036	3,542
$\Delta SEPU$ ($U_{i,t}$)	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: 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 6: 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.

Table 7: 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 8: 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.

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) Δvol Δemp Prime	(2) Δvol Δemp Old	(3) Δvol Δemp Prime -Old	(4) vol Gains Prime	(5) vol Gains Old	(6) vol Gains Prime -Old	(7) vol Loss Prime	(8) vol Loss Old	(9) vol Loss 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:

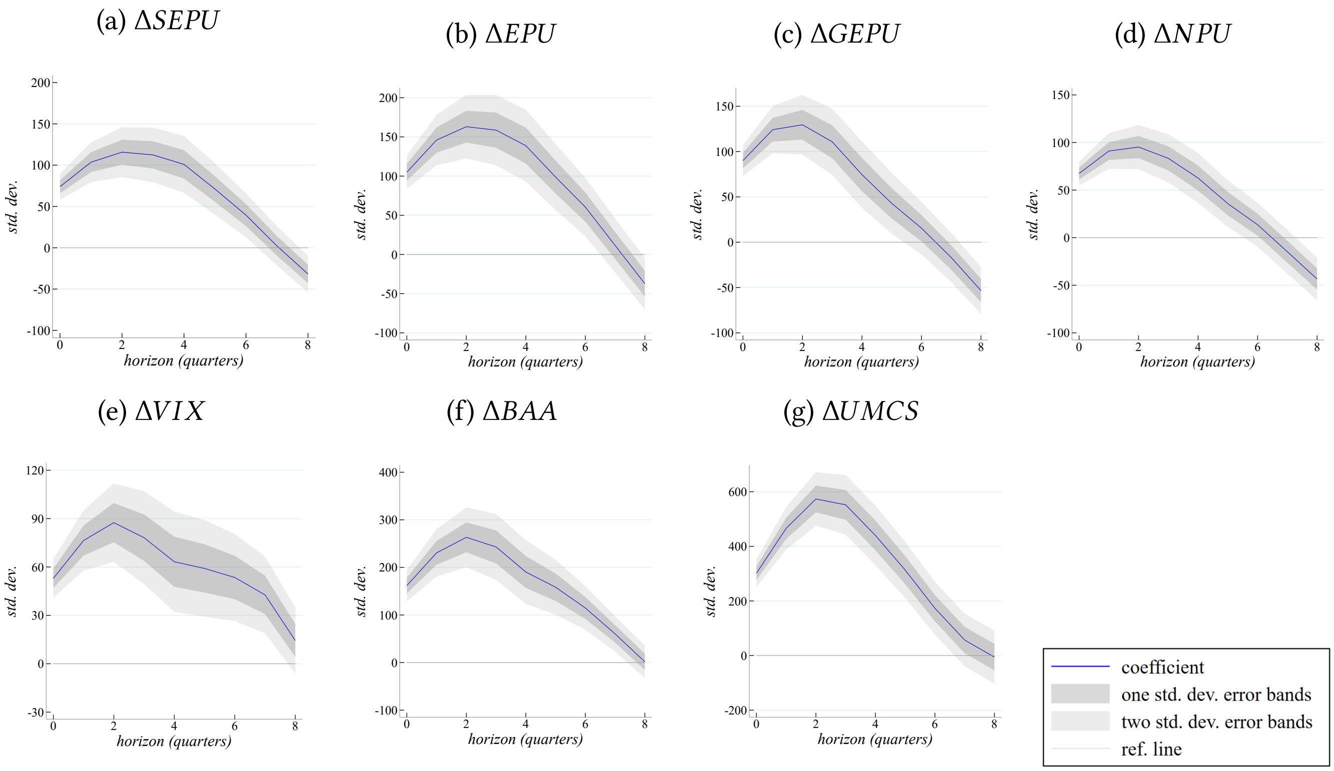
$$Y_{i,t+h} = \eta_i^h + \zeta_1^h N_t + \zeta_2^h \sum_{s=1}^{2} N_{t-s} + \zeta_3^h \sum_{s=1}^{2} Y_{i,t-s} + \kappa_{i,t+h}, h = 0, 1, ..., H \tag{18}$$

$Y_{i,t+h}$ 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:

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

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.

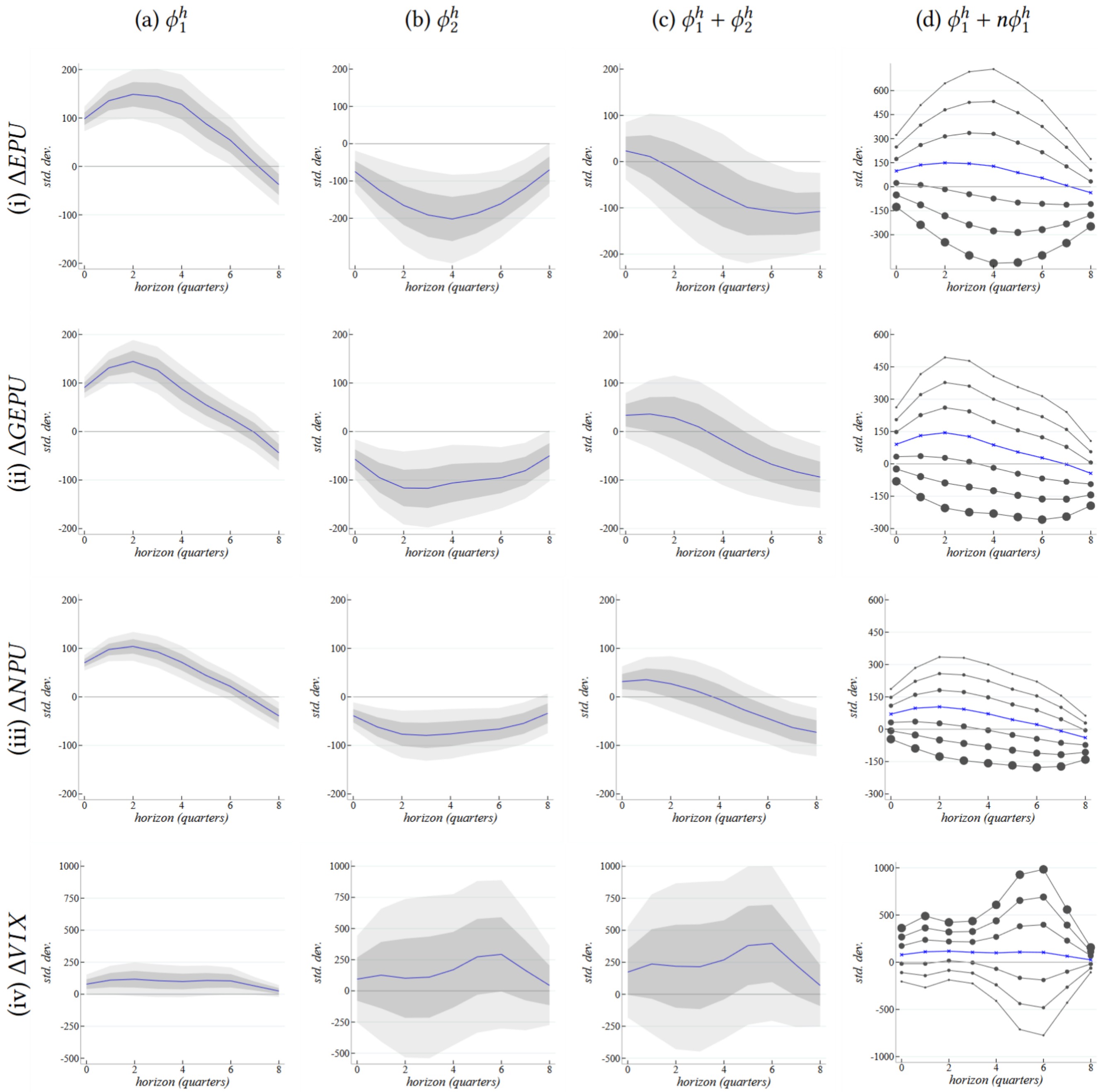
Estimation Results

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:

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

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

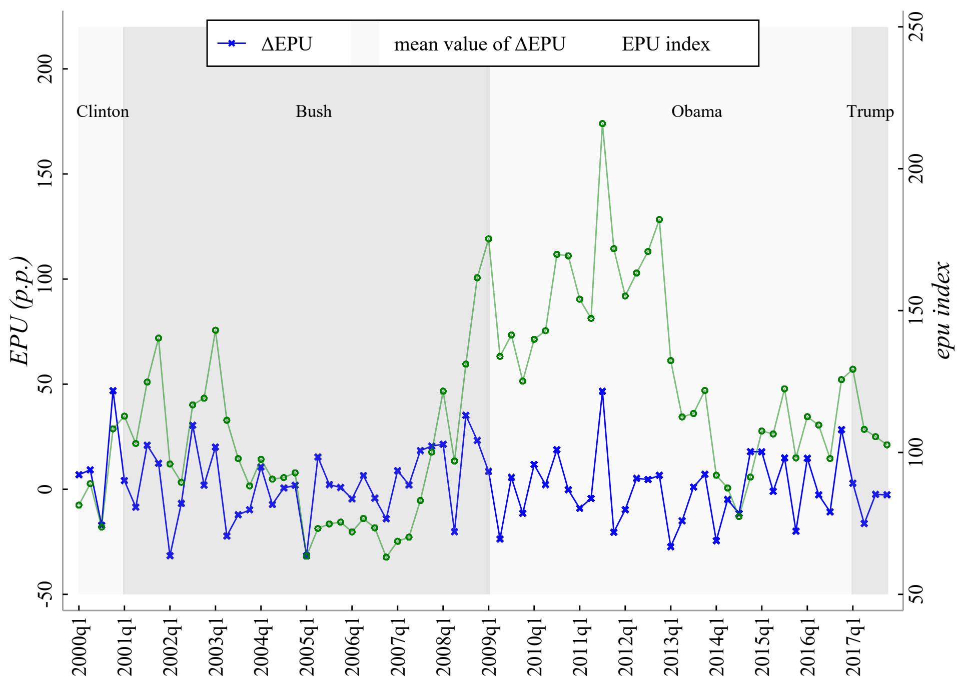
Note: This table presents the results of the baseline regression with different individual income variables.

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.

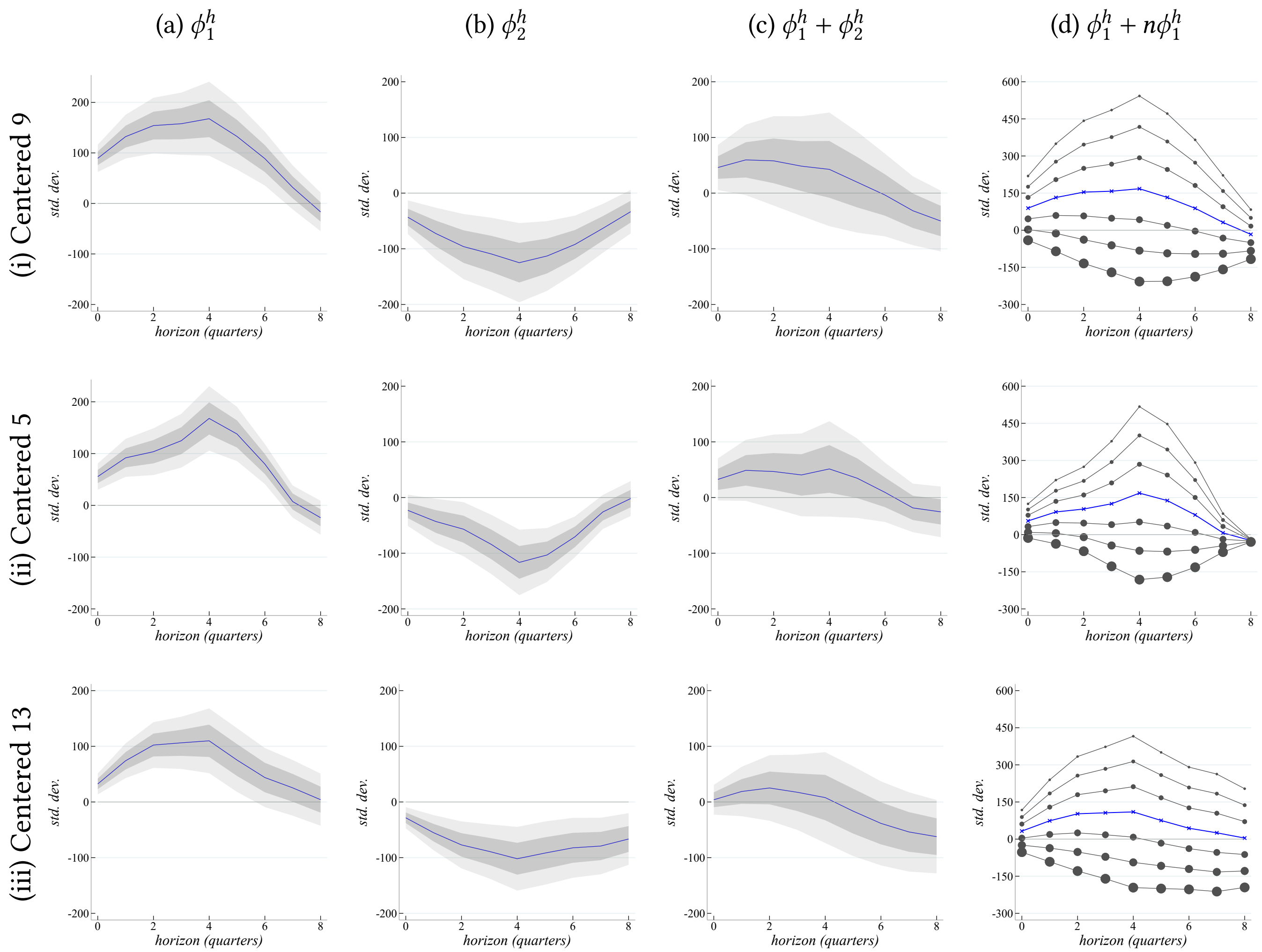
The IV regression results with the various outcome variable specifications are presented in Table A.13. Overall, the results remain consistent, with significance experiencing changes when specifying the outcome variable of interest in different ways. Specifically, when employing a 13-quarters, 9-quarter 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.

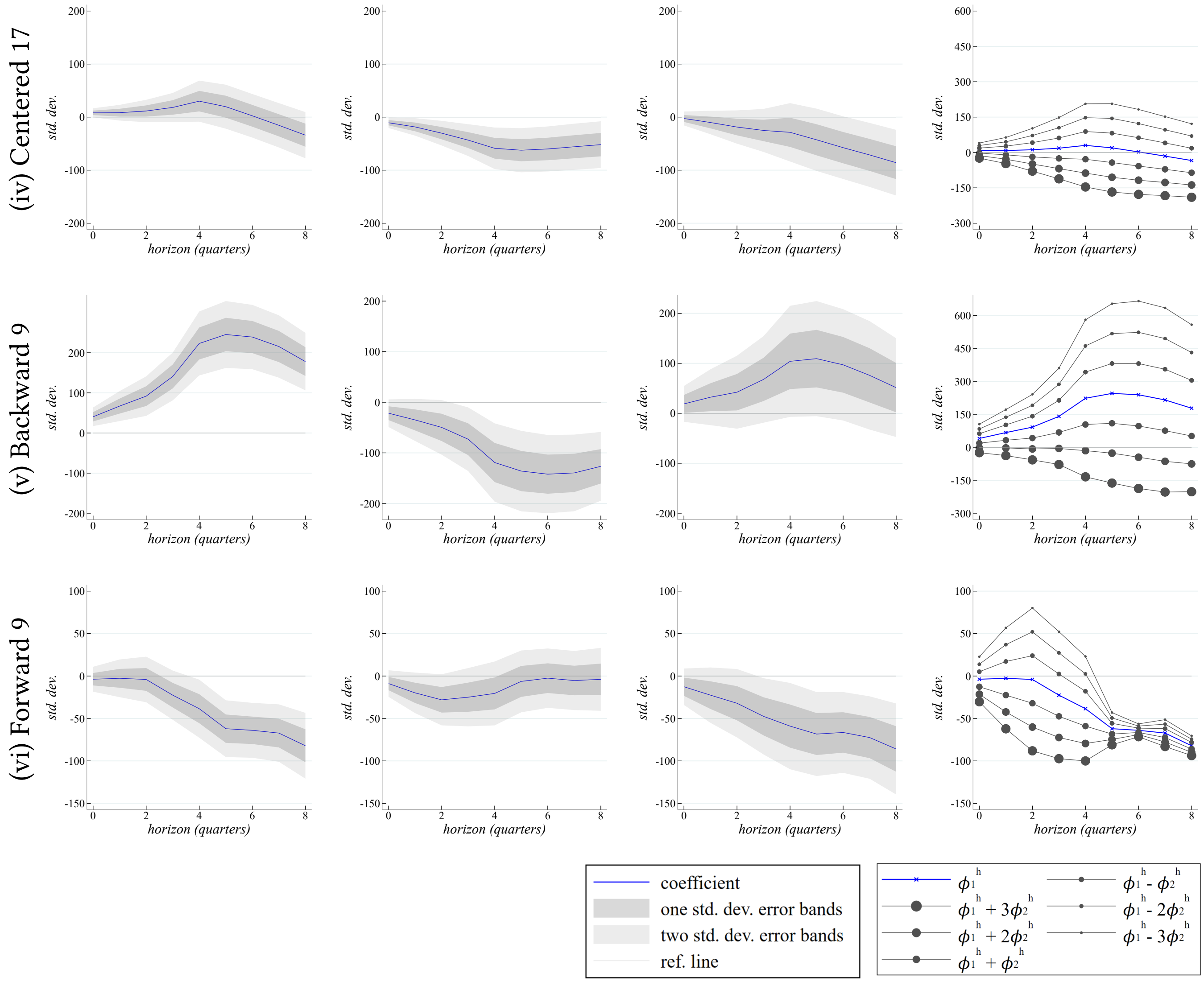
G.2 For LP-IV Estimation

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





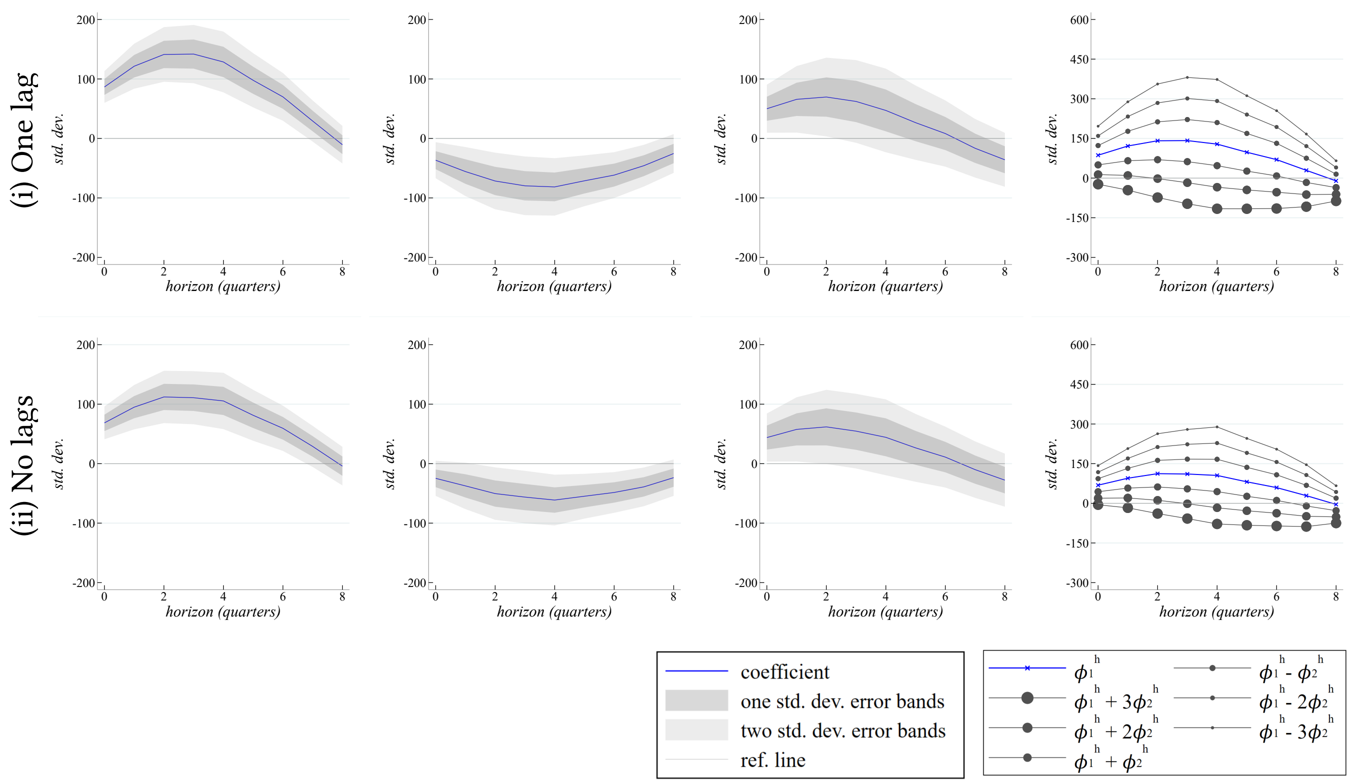
Note: The figures display the LP-IV IRF of cumulative cyclical employment volatility in response to state policy uncertainty shock that compares the effect from prime relative to that from old. The outcome variable is constructed using various numbers of windows and different calculations. Row i reports 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

(a) ϕ_1^h (b) ϕ_2^h (c) $\phi_1^h + \phi_2^h$ (d) $\phi_1^h + n\phi_1^h$



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/