Estimating the Effect of the Age Distribution on Cyclical Output Volatility Across the United States*

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I exploit the variation in demographic change across the United States to estimate the relationship between the age distribution in the population and the magnitude of cyclical output volatility. According to panel regression estimates the relative supply of young workers, or youth share, has a statistically significant effect on the volatility of state-by-state gross domestic product. Moreover, changes to the age distribution can account for up to 58% of the recent reduction in business cycle fluctuations, indicating a critical link between the youth share and output volatility.

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1 Introduction

Using panel data methods, I exploit the variation in demographic change across the United States to estimate the relationship between the age distribution in the population and the magnitude of cyclical output volatility. The empirical approach and general research question parallel Jaimovich and Siu (2009). According to my estimates the relative supply of young workers, or youth share, has a statistically significant effect on the volatility of state-by-state gross domestic product (GDP). Moreover, changes to the age distribution can account for a large portion of the recent reduction in business cycle fluctuations, indicating a critical link between the youth share and GDP volatility.

Differential demographic change across the panel of states identifies the youth share's effect on GDP volatility. However, endogeneity of the age distribution to output volatility causes a potential problem; cross-state migration due to current economic conditions likely bias the ordinary least squares (OLS) estimate in a regression of GDP volatility on the youth share. To address this concern, I explicitly instrument for the youth share with lagged birth rates. The youth share is highly correlated with past fertility decisions, and I do not think lagged birth rates affect the business cycle except through the age distribution. Shimer (2001) employs the same identification strategy to measure the youth share's effect on the unemployment rate, and similarly, Feyrer (2007) considers whether the age distribution affects aggregate productivity.

At the national level, cyclical volatility declined in the mid-1980's (Stock and Watson

2002). A few explanations for this so-called Great Moderation have been offered, but none has been satisfactory (see Davis and Kahn (2008) for a list of theories and why each fails to be completely convincing). Jaimovich and Siu (2009) hypothesize a new demographic based solution for the Great Moderation puzzle and estimate that the age distribution has a moderately large effect on output volatility in a panel of the G7 countries. I study variation across a single country and find an even larger youth share effect. The difference is not surprising because the correlation between the youth share and GDP volatility has been particularly high in the US relative to other countries.

This paper focuses on estimating the empirical relationship between demographics and the business cycle. Both the findings reported below and the results in Jaimovich and Siu (2009) lend support to the theory developed in Lugauer (2010) (see Jaimovich, Pruitt, and Siu (2010) for a related theory). Lugauer (2010) links the age distribution to the amplification of productivity shocks through a general equilibrium model with overlapping generations of workers and labor market search frictions. In the model, the share of young people in the population matters for two reasons. First, the willingness of firms to create new jobs depends on the age and productivity profile of the available pool of workers. Second, young workers experience more employment volatility, generating a simple composition effect. Clark and Summers (1981) first documented that employment volatility does vary by age group. More recently, Rios-Rull (1996) and Gomme, Rogerson, Rupert, and Wright (2004) have studied employment volatility by imbedding shocks in overlapping generations models, suggesting the age structure impacts the macro-economy. My work contributes to this on-going investigation into how employment differences across demographic groups affect output, particularly at cyclical frequencies.

Next, I present GDP volatility and youth share data. Section 3 contains the estimation results along with a discussion of the practical relevance and several robustness checks.

2 Data

I measure cyclical output volatility in a given year and state as the standard deviation of a centered 9-year window of de-trended, logged GDP. This method has become somewhat standard; see Jaimovich and Siu (2009). More specifically, I use state-by-state Bureau of Economic Analysis (BEA) GDP estimates. I convert the nominal BEA figures to real dollars using the BEA state-specific GDP deflators, which are available from 1977-2008. Then, I apply the Hodrick-Prescott (HP) filter with smoothing parameter 6.25 to the entire logged series.[1] Finally, I calculate the standard deviation of the 9-year rolling windows of the deviations from trend.[2] The entire process is done separately for each state. The youth share denotes the fraction of the population aged 20-54 under the age of 35 for a given state and year in the US Census information.

The BEA procedure for computing GDP by state changed after 1997. Appendix A describes how I combine the pre- and post-1997 GDP estimates and lists all the data sources. Alaska has been dropped due to lack of information. The resulting panel contains 1,200 total observations on 50 states (including the District of Columbia) from 1981-2004. The date range includes the Great Moderation. Large demographic changes transpired during this same period, but at different times in different states. The temporal and geographic variation in GDP volatility and the youth share drive the estimation strategy.

As mentioned in the introduction, migration patterns by age might react to cyclical output volatility causing simultaneity bias in the OLS estimates. For example, if younger workers leave states experiencing high GDP volatility, then the youth share would be artificially decreased. To address this concern and other potential omitted variables, I instrument for the youth share with lagged birth rates.[3] Shimer (2001) uses the same procedure. The state birth rates from 1947-1985 were obtained from assorted volumes of the United States Vital Statistics. The age distribution is closely related to fertility decisions made years earlier, with the correlation between lagged birth rates and the youth share averaging 0.86 for the 50 states. Past fertility decisions are unlikely to have depended on the magnitude of current business cycle fluctuations, and I think lagged birth rates only affect current GDP volatility by shaping the age distribution. Thus, birth rates make an excellent instrument for the youth share.

The differences in birth rates across states could have come from many sources. The post-WWII baby-boom impacted states in different ways, possibly because of draft patterns. Migration and economic growth varied by state and region; both might affect fertility. Other social and cultural factors affect fertility, even weather patterns have been known to alter birth rates. Whatever the cause, there exists ample variation to help identify the youth share's effect on GDP volatility.

To visualize the empirical strategy, Figure 1 depicts the data from 1981-2004 grouped into nine regions, each in a separate graph.[4] The left vertical axis measures GDP volatility, with the youth share and birth rates measured on the right. The annual values are expressed as ratios of the contemporaneous national average (analogous to year dummies) eliminating common trends. Furthermore, the three variables have been demeaned by region (analogous to region dummies) to account for sustained regional differences. Even with the year and region fixed effects removed, the timing and size of the demographic change varies across the nine graphs; the variation identifies the youth share's effect on GDP volatility. For example, the three variables display a hump shape in New England and the Mid Atlantic, but the demographic variables in the Mountain and Pacific regions have the opposite pattern. Meanwhile, the East North Central and West South Central were relatively stable until diverging in the late 1990s. None of the variables are monotonic. Importantly, lagged birth rates appear correlated with the youth share, giving birth rates power as an instrument. Also, GDP volatility tends to move with the demographic variables. The relationship looks strongest in the New England and Mid Atlantic regions. Next, I quantify the importance of this relationship by estimating the youth share's effect on GDP volatility across the full panel of states.

3 Results

I use standard panel data methods to estimate the youth share's effect on GDP volatility. Equation 1 captures the relationship of interest:

$$vol_{st} = \alpha_s + \beta_t + \gamma share_{st} + \varepsilon_{st}. \tag{1}$$

The variable vol_{st} stands for GDP volatility in state s during year t, and $share_{st}$ is the youth share in state s during year t. The vector α represents a full set of state dummy fixed effects to control for heterogeneity in GDP volatility levels across states. Similarly, the vector β represents a full set of year dummy variables to control for time varying fixed effects common to all states.[5] The term ε_{st} captures other sources of variation in GDP volatility, such as shocks to the local economy. Identification of the youth share effect, γ, comes from changes in the youth share over time not shared across states. The specification parallels the model studied in Jaimovich and Siu (2009).[6]

Ordinary Least Squares

The OLS estimate of γ equals 3.13 (column 1 in Table 1). The endogeneity of the age distribution to GDP volatility likely biases the OLS estimates downward. The residuals suffer from heteroskedasticity across states and serial correlation due to the overlapping structure of the GDP volatility measure. Throughout the paper, I report Newey-West robust standard errors with two lags to adjust for the heteroskedasticity and serial correlation.[7] The adjusted standard error for the OLS estimate of γ is 1.24.

Instrumental Variable

I instrument for the youth share with lagged birth rates. Equation 1 still captures the relationship of interest, and Equation 2 is the associated first stage:

$$share_{st} = \alpha_s + \beta_t + \pi birth_{st} + \nu_{st}. \tag{2}$$

The variable $birth_{st}$ stands for the sum of the birth rates in state s over the past 20 to 34 years, and I define all other variables as before. Column 2 in Table 1 reports the instrumental variable (IV) estimate and the first stage. Naturally, the youth share depends on lagged birth rates; the estimate of π equals 0.60 with standard error 0.05. The first stage R^2 is 0.97, and a test of the instrument's statistical significance admits a p-value less than 0.001. The strong first stage dispels any concerns about serious finite-sample bias problems (Bound, Jaeger, and Baker 1995). The first-stage point estimate has a simple interpretation. A 10 percentage point increase in the birth rates 20-34 years earlier implies a 6 percentage point increase in the current youth share. Shimer (2001) carried out the same first stage regression obtaining nearly identical results.

The IV estimate of γ equals 5.19 with standard error 2.18. The IV estimate greatly exceeds the OLS estimate. The downward bias in the OLS estimate most likely occurs because young workers tend to move out of states experiencing output volatility, mechanically decreasing the youth share. Measurement error in the youth share variable may also cause attenuation bias in the OLS estimate.

Column 3 presents the reduced form of GDP volatility regressed on the birth rate instrument. The coefficient estimate is about 40% smaller than the γ estimate in column 2, just as suggested by the first stage.

Figure 2 plots the estimated vector of β_t, the year dummy coefficients in Equation 1, as a time series with 1981 normalized to zero. The β's plunge after 1984 (the vertical line in Figure 2), the onset of the Great Moderation (Kim and Nelson 1999). The coefficients stay low thereafter, as does GDP volatility in the aggregate data. Figure 2 suggests that the year fixed effects account for the shared national trend, leaving the differential changes across states to identify γ.

Feyrer (2007) documents a connection between demographics and productivity growth. In turn, GDP growth might stabilize the economy, affecting the estimate of γ. Column 4 in Table 1 includes GDP growth for each state and year as an additional control in Equations 1 and 2. The resulting estimate of γ equals 5.78 with Newey-West (lag 2) adjusted standard error of 2.13.[8,9] This IV estimate represents the main result of the paper; the youth share has a large effect on GDP volatility. Although the standard error is not small, a null hypothesis of no effect can be rejected with better than 99% confidence in the baseline regression.

Discussion

The large standard error for the IV estimate can be blamed on the short panel and autocorrelation in the residuals. The 90% confidence interval for the baseline γ estimate goes from about 2.2 to 8.4; however, at even the low end of this range the youth share has an economically significant effect on GDP volatility.

Consider the recent Great Moderation and associated demographic change. In the aggregate US data, the youth share declined by more than 10 percentage points shortly after 1984. Meanwhile, GDP volatility fell by almost a whole percentage point or nearly 50% (Lugauer 2010). Substituting the baseline IV estimate of γ into Equation 1 implies the change in the youth share caused a $(10\% \times 5.78) = 0.578$ percentage point drop in GDP volatility. By this back of the envelope calculation, the age distribution can account for approximately 58% of the decline in GDP volatility.

Jaimovich and Siu (2009) and Lugauer (2010) estimate that the youth share explains a smaller (but still large!) $18 - 34\%$ of the Great Moderation, which corresponds to a γ estimate near the low end of my 90% confidence interval. Jaimovich and Siu (2009) study the same regression as Equation 1 using a panel of the G7 countries covering a slightly different time period. Their variable *share* includes the young and the very old, based on country-wide labor force shares. I use only the population youth share because this choice corresponds to the theory presented in Lugauer (2010), and employment volatility for older workers does not generally occur at business cycle frequencies in the US (Jaimovich and Siu 2009). Also, population shares are less likely to react to aggregate fluctuations than labor force participation.

The difference between my estimate and the Jaimovich and Siu (2009) findings might arise because GDP volatility and the youth share at the aggregate level have a greater correlation in the US than in the other countries Jaimovich and Siu (2009) study. For example, the relationship between the age distribution and business cycle fluctuations is less pronounced in France. Possibly, France has a less fluid labor market, and, according to Lugauer (2010), the youth share's effect on GDP volatility occurs through the labor market. Jaimovich and Siu (2009) provide an estimate of the average effect of the age distribution across countries; whereas, my findings apply specifically to the US. In a sense, I have put the Jaimovich and Siu (2009) hypothesis to a tougher test; demographic changes across states (e.g. the baby-boom) are more alike than across countries. Overall, I take the results as compelling evidence that the age distribution has an important effect on the amplification of the business cycle, while noting that the exact size of the effect remains uncertain and may vary by country.

Robustness Checks

To search for outliers, Figure 3 plots the $1,200$ residuals from regressing the youth share on the fixed effects and GDP growth against the residuals from regressing the birth rate instrument on the same controls. A striking finding emerges, the extreme observations mostly come from Utah. Column 1 in Table 2 reports the γ estimate omitting the 24 Utah observations. The estimate increases relative to the baseline estimate at 7.53 versus 5.78.[10] I continue to use the Utah data in the remainder of the paper and could find no other odd patterns by state or year.

HP-filtered time series may have excess endpoint volatility, which could affect the results. Column 2 in Table 2 reports the γ estimate with the observations from 1981 and 2004 dropped from the regression. The point estimate of 5.90 is about the same as the baseline estimate of 5.78.

As mentioned, the BEA changed the method for computing state GDP after 1997. Column 3 in Table 2 presents the IV regression without using the post-1997 data. The new panel still starts in 1981 but ends in 1993. The estimate of γ (11.72) increases substantially relative to the baseline estimate (5.78). Due to this dramatic difference, I next consider a regression where vol_{st} equals the standard deviation of the 9-year window of deviations from trend logged total employment for each state and year based on BEA data. The BEA did not change the methodology for computing total employment in 1997. Also, the employment data by state begins in 1969. Thus, the new panel begins in 1973, allowing for analysis during the period of increasing national volatility and increasing youth share.[11] The IV γ estimate equals 6.53 (column 4), which is statistically significant at better than a 1% level.[12]

I have experimented with different definitions for the variable $share_{st}$, which can affect the γ estimate. Including teenagers aged 15-19 in the youth share slightly increases the estimate. Not including 30-34 year-olds in the youth share decreases the estimate. Including older groups (55+) in the population (the denominator of the youth share) increases the estimate. I also performed the regressions employing more age group shares (20-34, 35-44, 45+) as explanatory variables to represent the age distribution with finer detail, omitting the oldest group to avoid colinearity. The coefficients on the age groups measure a shift out of the old into that age group. The oldest workers contribute the least to aggregate cyclical volatility. Thus, the coefficient estimate on the youth share (12.48) is larger than the baseline γ estimate (5.78). For brevity, I do not present the complete results. Instead, column 1 in Table 3 returns to the single youth share regressor ($share_{st}$) from the baseline regression, but I instrument with the birth rates lagged 20, 30, 40, and 50 years. Jaimovich and Siu (2009) use a similar approach. The first stage (not reported) is still strong. The IV γ estimate of 5.31 is slightly smaller than the baseline estimate of 5.78.[13] A null of no effect can be rejected with better than 99% confidence according to the Newey-West (lag 2) standard errors.

Table 3 also reports standard errors clustered by state in square brackets. As discussed above, construction of the GDP volatility variable introduces serial correlation into the residuals because most deviations from trend appear in nine consecutive years. Clustering standard errors by state can more flexibly control for the cross time error structure. Clustering increases the standard error to 2.69 in column 1, with the γ estimate statistically different from zero at a 95% confidence level.[14] Column 2 reports the regression results with GDP volatility (vol_{st}) calculated using the standard deviations from a 5-year (rather than 9-year) moving window, which re-uses the GDP data fewer times. The γ estimate of 4.85 is large in magnitude, though smaller than the baseline estimate of 5.78.[15] Column 3 repeats the analysis with the post-1997 data omitted. As with the baseline regression (column 3 in Table 2), the γ estimate (13.02) is far higher using the truncated panel. I conclude that calculating GDP volatility with a different size window does not greatly alter the main results.[16]

In columns 4 and 5 of Table 3, GDP volatility (vol_{st}) is constructed using 5 and 10 year intervals instead of rolling windows to further limit serial correlation.[17] The estimates of the youth share's effect on GDP volatility (5.07 and 4.23) are smaller using the intervals than in the baseline regression (5.78); however, a null hypothesis of no effect can be rejected with better than 90% confidence.[18]

Finally, column 6 presents the results when GDP volatility (vol_{st}) is calculated using the instantaneous method of Stock and Watson (2002). I use the same specification as Jaimovich and Siu (2009).[19] Specifically, the stochastic volatility model is:

$$\begin{aligned} \Delta y_t &= \sum_{j=1}^{p} a_{jt} \Delta y_{t-j} + s_t \omega_t, \\ a_{jt} &= a_{jt-1} + c_j \eta_{jt} \quad \text{and} \quad \log s_t^2 = \log s_{t-1}^2 + \zeta_t, \end{aligned}$$

where the shocks are independently distributed, and ω_t, η_{1t},..., η_{pt} are iid $N(0,1)$. The time-varying autoregressive parameters are estimated using Markov Chain Monte Carlo methods, which allows for the computation of the instantaneous standard deviation of output growth. See Stock and Watson (2002) for details. With this alternative definition of aggregate volatility, the IV estimate of γ equals 2.32 and is statistically significant at the 5% level according to the Newey-West standard errors. The regression does not include GDP growth as an independent variable. The coefficient cannot be directly compared to the baseline estimate because the dependent variable differs. If I repeat the back of the envelope calculation (from the discussion section) using the Stock and Watson volatility measure, then the γ estimate implies that the declining youth share accounts for about 50% of the Great Moderation.

The exact size of the youth share effect varies somewhat across the robustness checks presented in Tables 2 and 3. Grouping the data into 5 and 10 year intervals or using the Stock and Watson volatility measure decreases the estimate, while omitting Utah, dropping the post-1997 observations, or using employment volatility increases the estimate. In all cases, the main finding remains. The age distribution has a large effect on GDP volatility.

4 Conclusion

Recent demographic changes in the population provide an opportunity to uncover the age distribution's effect on the macro-economy. By applying standard panel data methods with lagged birth rates as an instrument, I estimate a strong statistical relationship between the youth share and GDP volatility across the United States. Moreover, I argue that this youth share effect has important economic ramifications, accounting for a significant portion of the Great Moderation.

Notes

[1]Jaimovich and Siu (2009) set the smoothing parameter to 6.25 for annual data. I use the same value to keep comparisons easy.

[2]For example, GDP volatility in Indiana during 1988 equals the standard deviation of the 1984-1992 deviations from the trend of the logged Indiana GDP series.

[3]For example, for Indiana in 1988, I instrument for the youth share with the sum of birth rates in Indiana from 1954-1968.

[4]As in Shimer (2001), I use the nine US Census Bureau divisions: New England (ME NH VT MA RI CT), Mid Atlantic (NY NJ PA), East North Central (OH IN IL MI WI), West North Central (MN IA MO ND SD NE KS), South Atlantic (DE MD DC VA NC SC GA FL), East South Central (KY TN AL MS WV), West South Central (AR LA OK TE), Mountain (MT ID WY CO NM AZ UT NV), and Pacific (WA OR CA AK HI) as regions. Figure 1 shows the average GDP volatility, youth share, and lagged birth rates across the states in each region.

[5]Regressing GDP volatility on just the fixed effects explains almost 86% of the variation from mean volatility. While the fixed effects explain a large portion of the variation, ample variation remains to estimate the youth share's effect as evidenced by Figure 1.

[6]Shimer (2001) employs a similar model to study the youth share's effect on the unemployment rate, and Blanchard and Simon (2001) use the same empirical approach to explore the relationship between inflation and output volatility.

[7]Jaimovich and Siu (2009) also report Newey-West standard errors with two lags. In the robustness checks, I examine the standard errors clustered by state.

[8]The estimated coefficient on GDP growth is negative and statistically signifigant at a 1% level.

[9]According to Castro and Coen-Pirani (2008), employment volatility varies by education level. Age and education are correlated, so I have also controlled for the share of the population with four years of college in each state and year using state educational attainment data from the Current Population Survey. The IV estimate for γ increases to 6.00, and the college share coefficient is not statistically different from zero.

[10]Throughout the robustness checks, Equations 1 and 2 define the IV regressions with the GDP growth variable added except where indicated. I do not report the OLS estimates of γ, which are always smaller than the IV estimates.

[11]Hawaii is dropped from the panel due to lack of lagged birth rate information.

[12]Dropping the pre-1981 observations and including GDP growth as an explanatory variable generates an IV estimate of 8.52. If the post-1997 observations are also omitted, then the estimate increases to 10.90. In both cases, the γ estimate is statistically significant at the 1% level.

[13]Hawaii and Texas were dropped from the sample due to lack of birth rate information. Omitting the post-1997 data leads to a larger γ estimate.

[14]The γ estimates in Table 2 are all statistically different from zero with at least 90% confidence when using standard errors clustered by state.

[15]I also estimated γ based on a 5-year moving window including years 1979, 1980, 2005, and 2006, and the results were similar.

[16]I repeated the analysis using other window sizes (6, 7, etc.) to compute GDP volatility. The resulting γ estimates are similar to the estimate based on the 5-year window.

[17]The demographic variables equal the simple average across the 5 or 10 annual observations. GDP volatility (vol_{st}) equals the standard deviation of the 5 or 10 deviations from trend during the interval, so no data points are reused when calculating GDP volatility.

[18]Note, the lagged birth rate instrument has a F-statistic less than 25 using clustered standard errors in the regressions based on 10-year intervals because of the small sample size.

[19]I thank Seth Pruitt for providing the algorithm to calculate the Stock and Watson (2002) volatility measure.

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5 Appendix: Data Sources

The annual state-by-state GDP data and deflators were obtained from the BEA web site:

http://www.bea.gov/regional.

The BEA provides the following cautionary note:

> "*There is a discontinuity in the GDP by state time series at 1997, where the data change from SIC industry definitions to NAICS industry definitions. This discontinuity results from many sources, including differences in source data and different estimation methodologies. In addition, the NAICS-based GDP by state estimates are consistent with U.S. gross domestic product (GDP) while the SIC-based GDP by state estimates are consistent with U.S. gross domestic income (GDI). This data discontinuity may affect both the levels and the growth rates of the GDP by state estimates. Users of the GDP by state estimates are strongly cautioned against appending the two data series in an attempt to construct a single time series of GDP by state estimates for 1963 to 2007.*"

To splice the two series together, I used the one year of overlap (1997) to calculate a factor based on the ratio of the two different values for GDP, for each state. Then, I multiplied the remaining years (1998-2008) by the state-specific factor.

The youth share was constructed based on information from the US Census, available for both census and non-census years for various age groups at:

http://www.census.gov/popest/archives/index.html.

When different Census data sources contained different population estimates for the same year, the most recent numbers were used.

The birth rates were obtained from assorted volumes of the United States Vital Statistics as compiled by the US Department of Health and Human Services. All data for the birth rate variables can be found on the Center for Disease Control web site at:

http://www.cdc.gov/nchs/products/pubs/pubd/vsus/vsus.htm.

I used the unadjusted birth rates to keep consistency over time.

The Current Population Survey March supplement was downloaded from the Minnesota Population Center web site at:

http://usa.ipums.org/usa.

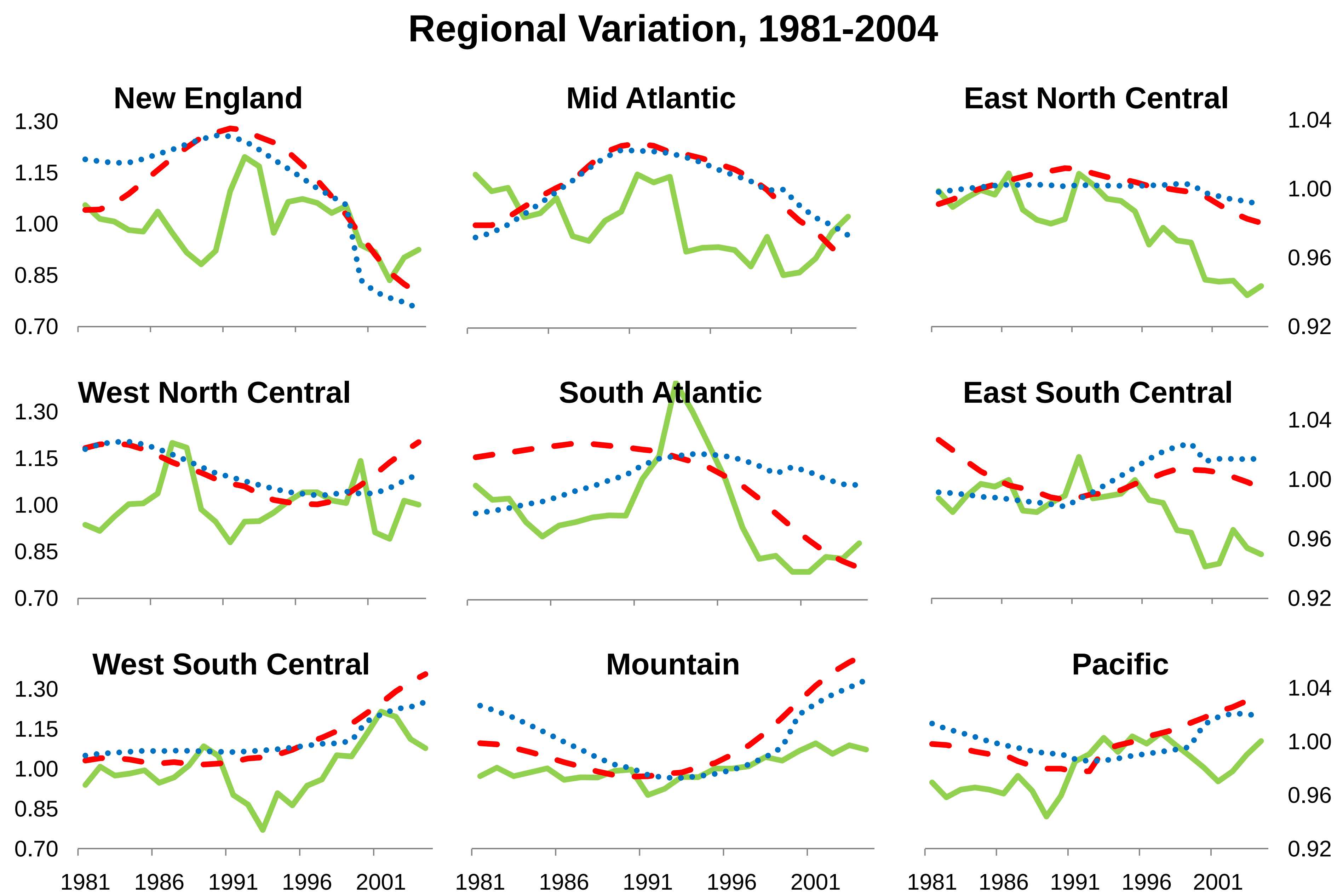

Figure 1: Demeaned regional cyclical GDP volatility (solid – left axis), youth share (dashed – right axis), and birth rates (dotted – right axis) relative to national contemporaneous average.

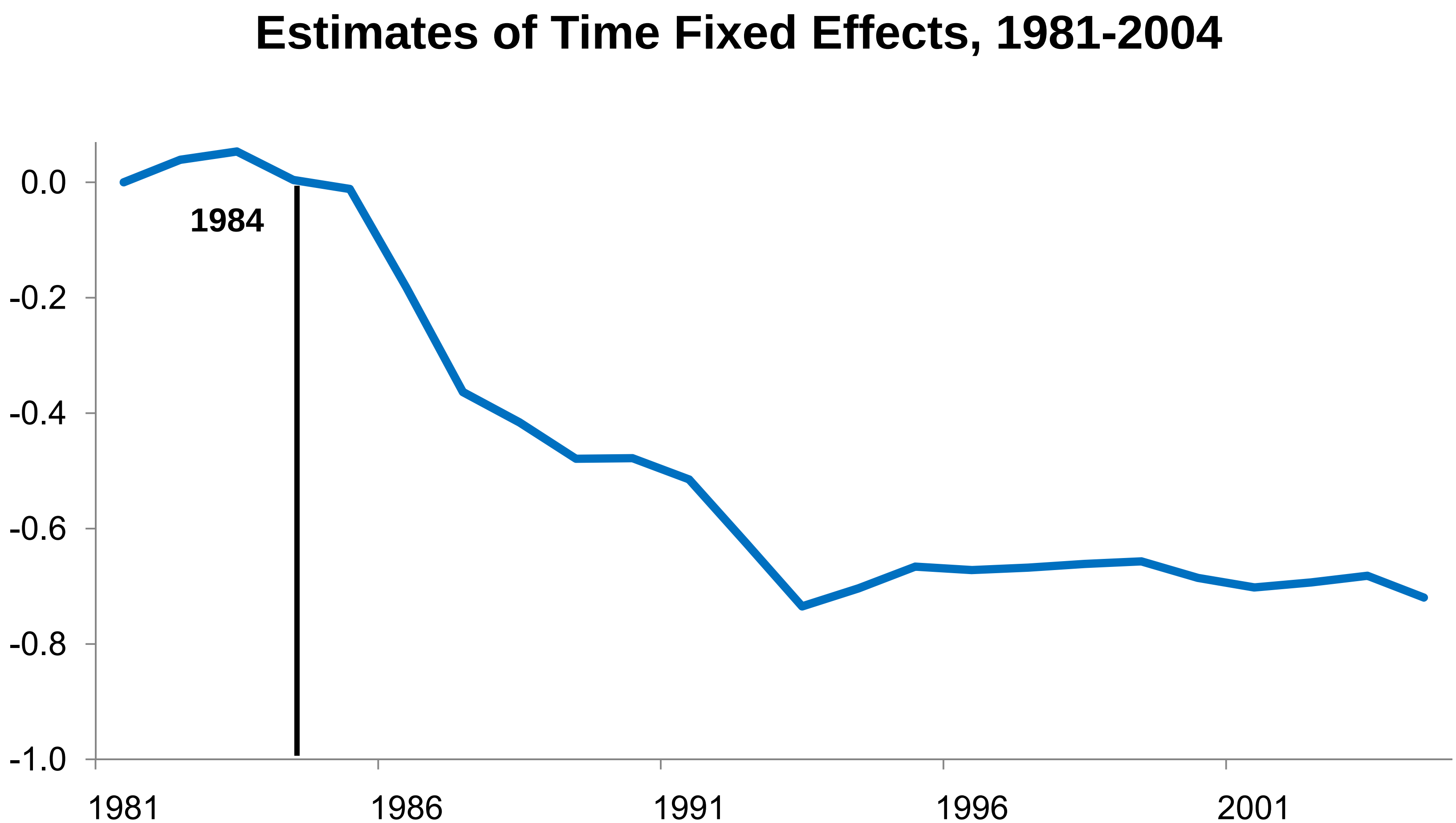

Figure 2: Point estimates of the vector of year dummies, β_t in Equation 1, with 1981 normalized to zero.

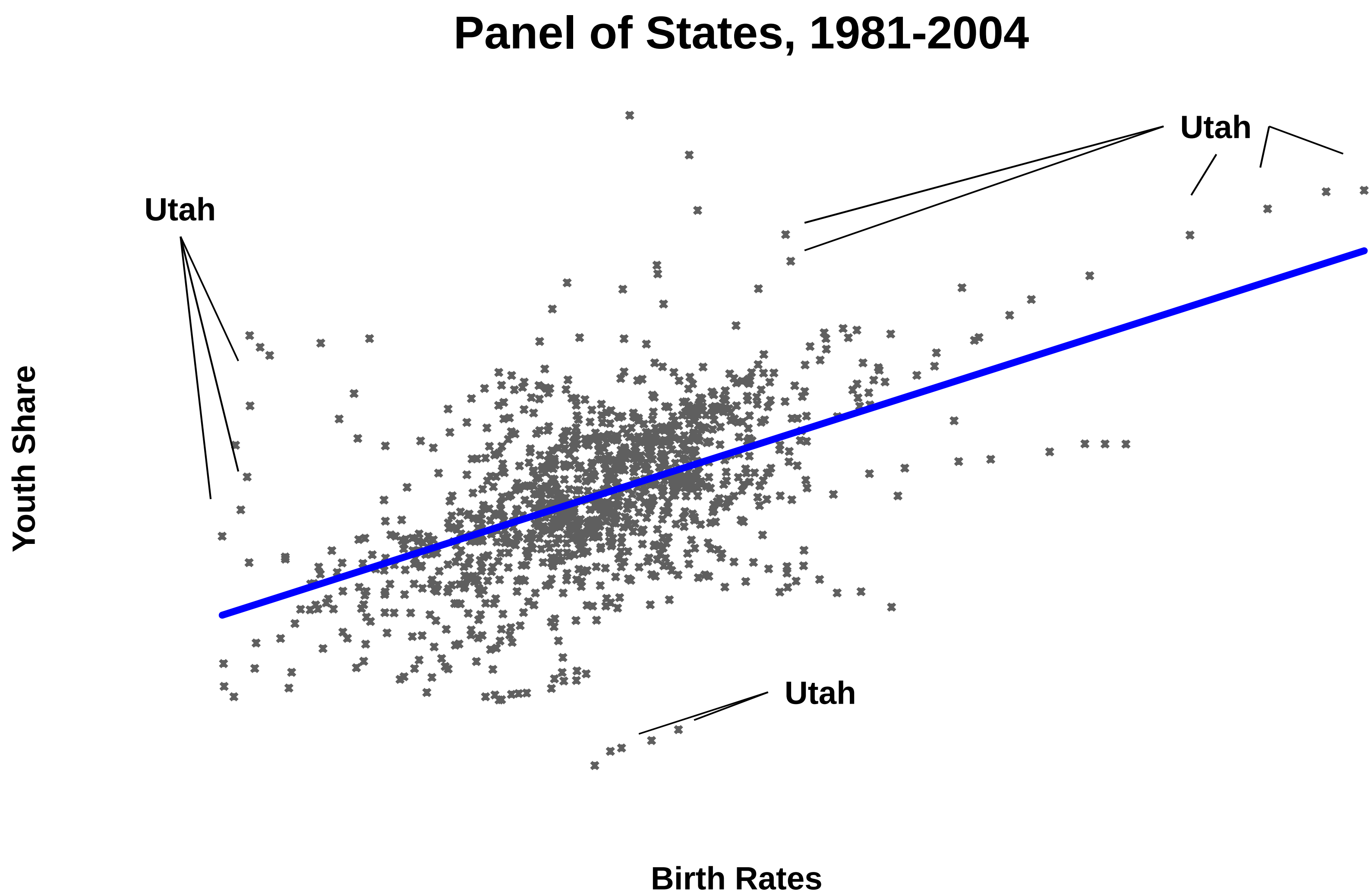

Figure 3: Residuals from Regressing the Youth Share and Birth Rates on the Fixed Effects and GDP growth with select observations from Utah indicated.

Table 1: Estimates of the Youth Share's Effect on GDP Volatility, 1981-2004

	Youth Share (*share*)			
	OLS (1)	IV (2)	Reduced Form OLS - *birth* (3)	w/ growth IV (4)
GDP Volatility (*vol*)	3.13 (1.24) **	5.19 (2.18) **	3.13 (1.25) **	5.78 (2.13) ***
R^2	0.90	-	0.88	-
First Stage:				
Lagged Birth Rates (*birth*)	-	0.60 (0.05) ***	-	0.60 (0.05) ***
p-Value	-	0.000	-	0.000
Observations	1200	1200	1200	1200

Notes: This table reports estimates for the parameter γ in Equation 1 with Newey-West standard errors (lag 2) in parentheses. The p-value is generated from the first stage regression based on Equation 2. The variables are defined in the text, and the Appendix lists the data sources. All regressions include a full set of state and year fixed effect dummies. Stars on the standard errors denote statistical significance of the parameter estimate at the * 10%, ** 5%, and *** 1% level.

Table 2: Robustness Checks for the IV Estimate of the Youth Share's Effect on GDP Volatility

	Youth Share (*share*)			
	Omit Utah (1)	Omit Endpoints (2)	Omit Post-1997 (3)	Total Employment (4)
Volatility (*vol*)	7.53	5.90	11.72	6.53
	(2.69) ***	(2.08) ***	(3.32) ***	(1.80) ***
First Stage:				
Lagged Birth Rates (*birth*)	0.55	0.61	0.81	0.48
	(0.11) ***	(0.06) ***	(0.09) ***	(0.04) ***
p-Value	0.000	0.000	0.000	0.000
Observations	1176	1100	650	1568
Years	81-04	82-03	81-93	73-04

Notes: This table reports IV estimates for the parameter γ in Equation 1 with Newey-West standard errors (lag 2) in parentheses. The p-Value is generated from the first stage regression based on Equation 2. The variables are defined in the text, and the Appendix lists the data sources. All regressions include a full set of state and year fixed effect dummies. Stars on the standard errors denote statistical significance of the coefficient estimate at the * 10%, ** 5%, and *** 1% level.

Table 3: Additional Robustness Checks of Baseline IV Estimate

	Youth Share (*share*)					
	Additional Instruments	5-Year Window		Intervals		Stock and Watson
		Full Panel	Omit post-1997	5-Year	10-Year	
	(1)	(2)	(3)	(4)	(5)	(6)
GDP Volatility (*vol*)	5.31	4.85	13.02	5.07	4.23	2.32
	(1.63) ***	(1.97) ***	(3.58) ***	(2.11) **	(2.21) *	(1.13) **
	[2.69] **	[2.75] *	[5.88] **	[2.19] **	[2.07] **	[1.41] *
First Stage:						
Birth Rates (*birth*)	-	0.60	0.74	0.49	0.43	0.58
		(0.05) ***	(0.08) ***	(0.08) ***	(0.09) ***	(0.05) ***
		[0.11] ***	[0.14] ***	[0.11] ***	[0.11] ***	[0.11] ***
p-Value	0.000	0.000	0.000	0.000	0.001	0.000
Observations	1200	1200	750	300	150	1400
Years	81-04	81-04	81-96	78-07	78-07	80-07

Notes: This table reports IV estimates for the parameter γ in Equation 1. Newey-West standard errors (lag 2) are reported in parentheses. The square brackets contain standard errors clustered by state. The p-value is generated from the first stage regression based on Equation 2 using the clustered standard errors. The variables are defined in the text, and the Appendix lists the data sources. All regressions include a full set of state and year fixed effect dummies. Stars on the standard errors denote statistical significance of the parameter estimate at the * 10%, ** 5%, and *** 1% level.