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Abstract

This study documents a general decline in the volatility of employment growth during the period 1960 to 2002 and examines its possible sources. A unique aspect of the analysis is the use of state-level panel data. Estimates from a pooled cross-section/time-series model indicate that aggregate and state-level factors each explain an important share of the total variation in state-level volatility. Specifically, state-level factors have contributed as much as 29 percent, while aggregate factors are found to account for up to 45 percent of the variation. With regard to state-level factors, the share of state total employment in manufacturing and state banking deregulation each contributed significantly to fluctuations in volatility. Among the aggregate factors separately identified, monetary policy, changes in the inventory-to-sales ratio, changes in the ratio of total trade to GDP, and oil prices significantly affected state-level volatility, although to differing degrees.

Employment growth volatility has been marked by three distinct patterns during the past 50 years. One is a substantial long-run decline, from about 0.7 percent per quarter in 1957 to about 0.2 percent in 2005. A second is the erratic pattern of the decline; periods of sharp decreases in volatility have alternated with periods of substantial increases. For example, volatility fell sharply between the mid-1950s and the mid-1970s, rose markedly from the mid-1970s to the mid-1980s, and declined sharply after the mid-1980s. A third pattern is the considerable cross-state variation in the extent of the declines. While volatility in most states has decreased, some states have experienced drops that exceed 60 percent and others have had declines of only 14 percent. Volatility actually rose in two states.

There is a large literature that examines the volatility pattern of aggregate economic variables and considers their determinants. However, there are few studies that use state level data to better understand the factors driving volatility. In this regard, we first document the variations in employment growth volatility across states since the mid 1950s. We then apply panel regression techniques to identify underlying sources of the fluctuations in volatility. The regressions are structured to capture the effects of aggregate factors, state-specific responses to aggregate factors, and idiosyncratic state developments, both time varying and time invariant.

We find that aggregate and state-level factors separately explain important shares of the total variation in state-level volatility. Specifically, aggregate factors are found to account for up to 45 percent of the variation, while state-level factors have contributed as much as 29 percent. Among the aggregate factors separately identified, monetary policy, changes in the inventory-to-sales ratio, changes in the ratio of total trade to GDP, and oil prices significantly affected state-level volatility, although to differing degrees. These findings support aggregate studies that have identified important roles for improved monetary policy and inventory management techniques in increased macroeconomic stability. In addition, we find that each of the aggregate factors has had significantly different state impacts. With regard to state-level factors, the share of state total employment in manufacturing and state banking deregulation each contributed significantly to fluctuations in volatility.

We believe the addition of state-level data to the analysis of volatility provides a number of benefits compared to using aggregate data alone. One benefit is the greater number of samples (48 for states compared with one in an aggregate study) afforded by using state-level data and the corresponding additional dispersion that allows more precise estimation of factors thought to influence fluctuations in volatility. Another benefit is the lack of endogeneity issues that can plague aggregate studies. For example, studies that attempt to attribute volatility changes to shifts in monetary policy need to separate the impacts of policy from the reaction of policymakers. Since monetary policy does not react to individual state-level developments, the issue of endogeneity is much less of a concern in a state-level analysis of volatility. Additionally, in aggregate studies any unobserved heterogeneity among states that affects volatility will be subsumed in the regression's error term. This unobserved state heterogeneity could lead to omitted variable bias if the error term is correlated with an included regressor. State deregulation of banking markets is a relevant example of how such omitted variable bias might work. Deregulation began in the late 1970s, the same period in which monetary policy was thought to have improved. Stock and Watson (2002), for example, attributed 20 percent to 30 percent of reduced volatility since the mid-1980s to improved monetary policy. Yet deregulation itself could have led to greater aggregate stability, and so failure to control for the effect of deregulation on volatility can cause the contribution of monetary policy to be overstated. The use of state-level data allows us to account for banking deregulation, something that is difficult to do when using aggregate data. Not all states deregulated their banking markets at the same time, and the staggered timing allows us to identify the effects of banking deregulation on volatility. Finally, rather than simply restricting aggregate forces to having the same impact on every state, the use of state-level data permits a test of whether the aggregate factors have differential state impacts, a phenomenon documented in other studies [e.g., Carlino and DeFina (1998, 1999)].

Measuring State-Level Employment Growth Volatility

The study focuses on employment growth because it is a widely used indicator of real activity, is available quarterly, and extends sufficiently far back in time to track longer-run movements in the series. Real state GDP was considered; however, consistent and reliable data are available beginning only in 1977. State personal income data exist for the entire study period but only in nominal terms.

This study measures state-level volatility following the approach in Morgan, Rime and Strahan (2004). Specifically, the quarterly growth rate of state employment growth is regressed on state dummies (a_i) and time period dummies (a_t) for the period 1956:3 to 2005:3:

$$\text{(1)} \qquad \text{Employment growth}_{\text{it}} = a_0 + a_i + a_t + \varepsilon_{it}.$$

Volatility is then measured as the absolute value of the regression error,

$$\text{(2)} \qquad \text{Volatility}_{\text{it}} = \left|\varepsilon_{it}\right|.$$

The volatility measure thus constitutes the deviation of employment growth in a given state-quarter from the average growth for a given state and from average growth in all states in a given quarter.[1] Our data are quarterly nonagricultural payroll employment from the Bureau of Labor Statistics (BLS).

The estimated equation has an adjusted R^2 of 0.9588. F tests indicate that both the state fixed effects are jointly significant ($p < 0.00$) and significantly different from each other ($p < 0.00$). F tests also reveal that the same results obtain for the time dummies: they are jointly significant ($p < 0.00$) and significantly different from each other ($p < 0.00$).

Figure 1 shows the average volatility of U.S. quarterly employment growth.[2] As can be seen employment growth volatility exhibited three distinct trends during the 1960 to 2002 period. Initially, volatility fell around 45 percent during the 1960s from a high of 0.67 in 1962 to 0.37 in 1971. Employment growth volatility then reversed its downward trend, rising to around 0.6 in 1978. This rise in volatility coincides with the generally poor economic conditions of the 1970s, a time during which the economy experienced rising inflation and slow growth. From the early 1980s on, however, volatility generally declined, dropping about 50 percent to 0.3 in 2002, as economic performance improved relative to the 1970s. Although most studies have concentrated on the final period of declining volatility, we believe that there is much to be gained by incorporating the fluctuations that occurred prior to the mid-1980s. Expanding the analysis to the whole

[1] Alternatively, volatilities can be computed using rolling standard errors or regression standard errors from rolling AR(1) models [e.g., Blanchard and Simon (2001).] As will be seen, using rolling standard errors complicates the panel data approach taken in the paper.

[2] The volatility series is smoothed using an eight-quarter moving average.

period thus adds valuable information about volatility that allows better identification of its underlying sources.

Because the data have a time-series dimension, two concerns must be addressed. First, it is necessary to check for stationarity in the estimated ε_{it}. Two alternative panel unit root tests were performed. The first is the technique of Levin, Lin, and Chu (2002), which restricts all states to a common unit root. The second, developed by Im, Pesaran, and Shin (2003), allows the unit root process to vary across states. Both tests were done with and without trends. All regressions include four lags of the dependent variable to account for autocorrelation. The nulls of unit root processes were rejected in all cases at the 1 percent level.

Second, as was mentioned, many researchers have identified a break in volatility of the aggregate economy that occurred around 1984 [e.g., Kim and Nelson (1999), Stock and Watson (2002), and McConnell and Perez-Quiros (2000).] Alternatively, Owyang and Wall (2005) present evidence of structural breaks in state-level employment growth volatility that occurred at widely differing dates. We therefore tested each of the state volatility series for the possibility of a structural break using the Andrews-Ploberger (1994) test for a linear regression. Each state series is modeled as an AR(1) process. The test involves splitting the sample into two sub-periods for a given break date. A Chow test statistic is then calculated to test the equality of coefficients before and after the break. This is done for all possible break dates so as to identify the break endogenously. A structural break is identified by the break date with the largest test statistic value. Significance is determined using values tabulated by Andrews-Ploberger (1994).

The Andrews-Ploberger tests indicate structural breaks in all but five of the state series.[3] The results are displayed in Table 1. The table contains the identified break dates for each state, along with each state's average volatility in the periods before and after the state's identified break date. The declines in volatility were widespread across states, with volatility in only two states – New York and Texas – rising (Table 1). The sizes of the declines varied considerably. The largest and smallest percent declines differ by a factor of five, with Nevada showing the largest decline (66 percent) and New Hampshire and Utah the smallest (13 percent).

The information in the Table 1 is reproduced in the form of distributions in Figure 2 and Figure 3. Figure 2 shows a histogram of the break dates. Consistent with Owyang and Wall (2005), the findings reveal considerable variation in break dates across states, emphasizing the value of examining trends in volatility at the sub-national level. The earliest break dates occurred in 1964 (Utah, Pennsylvania, and Mississippi), while the latest occurred in 1996 (Nevada). The majority of structural breaks occurred between the early 1980s and the early 1990s. The median break date was found to be 1985:2, roughly consistent with the structural break date identified in studies of macroeconomic volatility.

Figure 3 displays kernel density estimates of the frequency distributions for the average state-level volatilities in the periods before and after the break dates identified for each state.[4] The frequency distributions illustrate a key property of volatility over the

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[3] The five states with no identifiable breaks are Georgia, Massachusetts, North Carolina, New Jersey, and South Carolina.
[4] Given a kernel K(u), the estimated density function for x is:

$$\hat{f} = \frac{1}{nh}\sum_{i=1}^{n} K\left[\frac{x - X_i}{h}\right]$$

sample period: the distribution of state-level employment growth volatilities shifted markedly to the left. That is, state employment growth volatility has decreased. The cross-state average volatility fell by over 40 percent, from 0.52 in the pre-break period to 0.30 during the post-break period.

III. Sources of State-Level Employment Growth Volatility

Having documented the substantial and disparate declines in state employment growth volatility, this section turns to an examination of the possible sources. As mentioned earlier, the fact that most states experienced volatility declines during the sample period suggests that part of the variance might be due to common state responses to aggregate shocks. A large literature has identified several possible factors that have influenced volatility in the postwar period. Stock and Watson (2002) group these factors into three broad categories. One category comprises improved macroeconomic policy, in particular improved monetary policy, and shifts in its anti-inflationary stance [Clarida, Gali, and Gertler (2000), Orphanides (2001), Leduc, Sill, and Stark (2007), Stock and Watson (2002), Leduc and Sill (2007)]. The second category considers structural change in the economy. Potential sources of structural change that have been identified in the literature include changes in industrial composition, such as a shift from manufacturing to services [Blanchard and Simon (2001)], changes in inventory control practices [McConnell and Perez-Quiros (2000) and Kahn, McConnell, and Perez-Quiros (2003)], changes in the stability of total factor productivity growth and labor productivity [Stock and Watson (2002) and Leduc and Sill (2007)], innovations in financial markets

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where n is the number of observations in the sample and h is the bandwidth. The points at which the density is estimated are indicated by x and the data by Xj. The estimates use the Gaussian kernel and an optimal bandwidth that minimizes the mean integrated square error.

[Blanchard and Simon (2001)], and increased economic integration via expanded trade [Gordon (2005)]. Good luck in the form of smaller shocks hitting the economy is the third category identified by Stock and Watson (2002).

In addition to common state response to aggregate shocks it's likely that states have their own unique response to common aggregate shocks. For example, Carlino and DeFina (1998, 1999) document that common monetary policy shocks caused differential responses in employment and income across states, responses that varied systematically with the states' industrial structures. An advantage of this study is that we allow states to respond differentially to common national shocks. It's also likely is that unique state-level forces, such as differences in laws, industrial structures, labor force compositions and other demographic dimensions of the population, could account for some of the cross-state variation in volatility. To the extent that these unique state-level forces are time invariant, we can use state fixed-effects to account for them.

States can also undergo unique changes over time that affect volatility. State banking deregulation that began in the late 1970s is an important case in point. Interstate banking may have smoothed credit flows and made state economies much less sensitive to the fortunes of their own banks. However, states deregulated their banks at different dates, causing volatility in state economic activity to change asynchronously [Morgan, Rime, and Strahan (2004).][5] Similarly, state-specific changes in industrial structure or demographic shifts due, say, to immigration, can potentially alter the time series profile of a state's employment growth volatility.

[5] In 1978, Maine was the first state to pass a law that allowed entry by bank holding companies from any state that reciprocated by allowing Maine banks to enter their banking markets. Following Maine's lead, states deregulated in waves, with the bulk of states approving legislation to allow deregulation between 1985 and 1988. With the exception of Hawaii, all states allowed interstate banking by 1993.

Accounting for idiosyncratic aspects of state economies is important not only because it can help to explain state-level employment volatility changes, but also because not doing so can lead to an overestimate of the impact of national factors. Stock and Watson (2002), for example, attributed 20 percent to 30 percent of reduced volatility since the mid-1980s to improved monetary policy, while Leduc and Sill (2007) place the estimate at about 15 percent. But financial deregulation occurred at roughly the same time that monetary policy is supposed to have improved. Since deregulation itself might have lowered state-level employment volatility [Morgan, Rime, and Strahan (2004)] and since it is not possible to control for state-level financial deregulation using aggregate data, monetary policy's role in lowering volatility may have been overstated.

In sum, state-level employment growth volatility could have been driven by states' common responses to aggregate shocks, states' differential responses to aggregate shocks, as well as state-specific forces. The next section develops an empirical approach designed to capture these three broad determinants of volatility.

IV. Empirical Model and Estimation

The analysis in this study uses a two-way fixed effects (state and time) panel data model to analyze quarterly data on state employment growth volatility for the period 1960 to 2002.[6] State-level volatility is measured as in equation (2).[7] Because the volatility series are stationary they are used in level form. Explanatory variables include

[6] A Hausman test indicated that a two-way fixed effects specification, both for time and states, was preferred to a two-way random effects specification.

[7] Alternatively, volatility could be measured using 20-quarter rolling standard errors as others have [e.g., Blanchard and Simon (2001)]. However, this approach complicates the econometric analysis as it results in overlapping samples and artificially builds autoregressive patterns in the data. To mitigate this problem, it would be necessary to construct non-overlapping samples of volatilities, which would limit the panel to eight separate periods, insufficient for the analysis undertaken in this paper.

aggregate and state-level factors. All aggregate factors are permitted to have distinct state-level effects.

Aggregate variables. An advantage of a panel approach is that we can account for the common effect of all aggregate forces on state volatility using time fixed effects. The model is specified so that macro policy (monetary policy) and structural change (e.g., changes in inventory control practices and changes in the stability of labor productivity growth) and openness to foreign trade, each have a differential effect on state volatility. This is accomplished by interacting each of the aggregate variables to be identified with the state dummy variables. Additionally, the price of oil, interacted with state dummy variables, is included in our empirical model given its historically important role in macroeconomic performance [Hamilton (1983, 1996, and 2003)].

Monetary policy is measured using the federal funds rate, which is standard. Following Hamilton (2003), the oil price shock at time *t* is measured as the net oil price increase over the previous 12 months. Denote the spot price of West Texas Intermediate oil as p_t^o. The net oil price increase ($\tilde{p}_t^o$) is defined as

$$\tilde{p}_t^o = \max\left(0, \frac{p_t^o - \max[p_{t-1}^o, p_{t-2}^o, \ldots, p_{t-12}^o]}{\max[p_{t-1}^o, p_{t-2}^o, \ldots, p_{t-12}^o]}\right)$$

This measure of oil-price shocks appears to demonstrate a more stable link to real activity then does the actual price of crude oil over the postwar sample. Productivity growth is calculated as the log difference of labor productivity, obtained from the Bureau of Labor Statistics. The trade variable equals the sum of nominal imports and exports divided by nominal GDP. The trade ratio has trended up over time, so the series was first-differenced for use in the estimations. Inventory management methods are proxied using the inventory-to-sales ratio. The series trended up and then plateaued in the sample period and so was also first-differenced to ensure stationarity.

The time series of the aggregate variables are shown in Figures 4 through 7. Examination of these figures reveals that the series appears stationary and therefore appropriate for use in the estimations. In addition, the volatility of each series has fallen over time, suggesting a possible role for these variables in the state-level volatility declines.

State-level variables. An additional advantage of a panel approach is that we can use state fixed effects to account for time invariant idiosyncratic state level factors that can influence state volatility. As is common, the impacts of all aggregate forces on state volatility are captured using time fixed effects. Time invariant state-level influences are modeled using state fixed effects. As we have indicated, a state's industrial structure and financial deregulation are two important forces that have varied over time. Each state's manufacturing employment as a share of its total employment is used to capture changing industrial structure. Likewise, we use a set of state-specific dummies to indicate when a state allowed interstate banking. The dummies equal zero before a state experienced financial deregulation and unity otherwise. The dates of state-level deregulation are from Morgan, Rime, and Strahan (2004). Finally, the model includes state-specific time trends to capture state factors that change gradually over time, such as demographic shifts in state populations.

Empirical specification. The sample consists of quarterly data covering the period 1960 to 2002.[8] The sample contains 8,256 observations: 172 quarters of data for 48

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[8] Owing to the conversion of the industrial classification coding system to NAICS, consistent data for manufacturing share are available only through 2002.

states. Contemporaneous and lagged values of each explanatory variable are used to allow for delayed or persistent impacts. Moreover, the model permits both the intercept and the slope coefficients to take different values for each state and, for a given state, different values before and after the structural break dates identified for each state's volatility series.

The model takes the form (abstracting from the lags):

$$
\begin{aligned}
(3) \qquad & |\varepsilon_{it}| = \alpha_0 + state_i(1+break_{i,t}) + \alpha_t + \beta_i T_i + \sum_{i=1}^{47} \nu_i (1+break_{i,t}) manshare_{i,t} + dreg_{i,t} \\
& + \sum_{i=1}^{47} \sum_{m=1}^{4} \delta_{m,i}(1+break_{i,t})(state_i * Z_{m,t}) + \nu_{it}
\end{aligned}
$$

where: $|\varepsilon_{it}|$ is the absolute value of quarterly employment growth fluctuations; t indexes time (quarters), i indexes the 48 states, and m indexes the subset of aggregate explanatory variables to be estimated; $break_{i,t}$ is a dummy variable, taking the value 0 before a state's identified break date and 1 after; α_t is a quarterly time dummy; T_i is a time trend for state i; $state_i$ is a dummy variable equal to 1 for state i and 0 otherwise; $manshare_{i,t}$ is the share of state i's total employment in manufacturing; $dreg_{i,t}$ is the deregulation dummy for state i; and, Z_t is the set of national variables that are interacted with the $state_i$.

Estimation and Results. Coefficients for equation (3) are obtained using a robust OLS estimator.[9] A series of regressions were run to determine the appropriate lag length for each variable.[10] Based on the results from these regressions, four lags of the oil price

[9] We estimated the model using a Prais-Winsten estimator that corrects for both state-level heteroskedasticity and state-specific first-order serial correlation. The result for the robust OLS regressions are virtually identical to those obtained using the Prais-Winsten estimator. We choose the robust OLS estimation since it is appropriate for the accounting exercise conducted in this analysis.
[10] The usual AIC or BIC could not be used due to the panel structure of the data. Instead we estimated equation 3 without the state interactions on the macro variables, using five lags of each macro variable and of the state manufacturing share. State interactions are ignored so that average effect can be measured. The contemporaneous plus all lags up to the maximum significant lag for a variable were used. For

variable, three lags of the manufacturing share, federal funds rate and change in the inventory-to-sales ratio, and two lags of the change in the total trade ratio are used, along with their contemporaneous values.[11]

Due to the large number of state interactions, lags, and state and time fixed effects, it is not practical to display the individual estimated coefficients. Instead, results are summarized in the form of F tests. Test statistics are shown in Table 2 for both the joint significance and equality of coefficient values for each of the variables in the model.

As can be seen, each state-level variable is found to be jointly significant at the 1 percent level. Similarly, F tests for the equality of coefficients are rejected for each variable in the model. These findings are especially interesting since previous studies of volatility have ignored state-level influences. They are also interesting particularly with regard to deregulation and manufacturing shares. The joint significance of the deregulation dummies (F = 4.31) provides new support for the findings of Morgan, Rime, and Strahan (2004) in that the present model has considerably more controls than theirs. In addition, Morgan, Rime and Strahan (2004) restricted deregulation to have the same effect on each state. As already indicated, our results show that these restrictions are unwarranted. An F test of the null hypothesis of the equality of 48 estimated coefficients on the deregulation variable is soundly rejected (F = 4.36).

The finding that the manufacturing shares variables are jointly significant and significantly different from one another is notable since, to our knowledge, no other study has found changing industrial structure to be correlated with increased stability of the of

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instance, if the fourth lag of the oil price was significant, the contemporaneous through the fourth lag were included in the estimation.

[11] Neither the contemporaneous value nor any lags of labor productivity growth were significant; hence, the variable was excluded from all regression.

the economy. The inability of previous studies to uncover a significant correlation between declining manufacturing share and greater economic stability might reflect the past focus on explaining the one-time structural aggregate break identified in the mid-1980s. Manufacturing employment shares have been decreasing steadily for decades and have not experienced a sudden one-time decrease. So while they might not reasonably explain a one-time change in volatility, they do appear to have contributed to the longer run, more continuous, volatility changes examined in this study.

The results also offer support for the aggregate variables. The time dummy variables are jointly significant (F = 2.74) and significantly different from one another (F = 2.72). In addition, the results in Table 2 indicate that changes in monetary policy, fluctuations in oil prices, increased international trade, and improved inventory management techniques have all had differential effects on state level volatility. Importantly, these aggregate variables matter even when all are simultaneously considered. The results also validate the initial determination of the break dates for each of the states based on the Andrews-Ploberger tests. The break variables themselves are highly significant, indicating that the structural break partly took the form of a shift in the average levels of state volatility. In addition, the interactions of the break variables with the federal funds rate, state manufacturing employment share, the change in the inventory-to-sales ratio, oil prices, and the total trade ratio are similarly significant.

The findings discussed so far establish the statistical significance of both state-level and aggregate influences on state employment volatility, and the importance of recognizing states' differential responses to aggregate factors. The question remains as to the economic significance of the factors. That is, how much of the actual variance in state-level employment volatility do the different variables account for?

Accounting for volatility. An answer to the question is provided with a number of auxiliary regressions, which are used to generate bounds on the size of the contributions of each variable or subset of variables. Consider the following auxiliary regression for state-specific factors.

$$|\varepsilon_{it}| = \alpha_0 + state_i(1+break_{i,t}) + \beta_i T_i + \sum_{i=1}^{47} \nu_i (1+break_{i,t}) manshare_{i,t} + dreg_{i,t} + \psi_{it} \qquad (4)$$

Equation (4) contains only the state-specific factors ($state_i$, T_i, $state_i * manshare_{i,t}$ and $dreg_{i,t}$) as explanatory variables, allowing all coefficients to differ before and after the estimated state break dates. The R^2 from this regression gives the upper bound for the contribution of the state-specific factors, since all co-variance between them and the excluded aggregate variables is allocated to the state-specific factors. We refer to the R^2 from Equation (4) as R_U^2.

An estimate of the lower bound for the contribution of state-specific factors is generated by estimating a second auxiliary regression that includes only the interacted macroeconomic variables and the time dummies, again allowing coefficients to vary across the break dates. The R^2 from this equation, called R_M^2, maximizes the measured contribution of the macro variables since all co-variance with the now excluded state-specific factors is ascribed to the aggregate variables. Thus, subtracting R_M^2 from the R^2 of the full equation, R_{ALL}^2, yields the lower bound for state-specific variables, referred to as R_L^2 (i.e., $R_L^2 = R_{ALL}^2 - R_M^2$). An analogous exercise is conducted to get the upper bound and lower-bound for the contribution of the macroeconomic variables ($state_i * Z_{m,t}$ and α_t,) and for individual state-level and aggregate variables.

The results of this exercise are shown in Tables 3 and 4. Table 3 presents estimates of the combined effects of the macro variables versus the combined effects of state-level variables. Panel A of the table presents the R^2_{ALL} for the full equation and for the equations that contain only state-specific variables and macro variables, respectively. R^2_{ALL} indicates the full model explains 57 percent of the total variation in state-level employment volatility. The R^2s for the state-specific and macro variables give the maximum contributions of each set of variables. As described above, subtracting each of these from the total R^2_{ALL} yields the minimum contribution of each set of variables. The results of these calculations are shown in Panel B of the table.

As can be seen, the range of potential contributions from the state-specific factors is 11 percent to 29 percent. The range of contributions for the macroeconomic variables is between 27 percent and 45 percent of the total variation in employment growth volatility. Consequently, macro variables have likely played a more important role than the state-specific factors. However, the contributions of state-specific factors, which have received little attention in the volatility literature, appear important. At a minimum, state-specific factors account for about 20 percent of the total explained variation in volatility (11%/57%).

Table 4 contains the range of contributions of each of the individual variables used in the regression. Among the macro variables, monetary policy accounts for between 8 percent and 24 percent of the variation.[12] The range for monetary policy is similar to the estimated explanatory power of monetary policy found by Stock and Watson (2002) and Leduc and Sill (2007) when examining the post-1984 decline in GDP volatility. The change in the inventory-to-sales ratio accounts for between 6 percent and 11 percent, while oil prices explain around 5 percent to 14 percent. Thus, they each appear to play a relatively important role. This finding complements those of McConnell and Quiros-Perez (2000) and Kahn, McConnell, and Quiros-Perez (2002) who find a significant role for inventory-to-sales ratio in explaining the structural break in aggregate volatility. The change in the total trade ratio accounts for somewhat less variation, about 2 percent to 7 percent.

The results show that each of the state-level variables potentially has played an important role. The change in states' manufacturing shares could explain up to 17 percent, while deregulation of interstate banking could explain an additional 9 percent. State fixed effects account for between 2 percent and 13 percent, while the state-specific time trends explain between 1 percent and 12 percent. The results once again suggest the importance of incorporating state-level factors into an analysis of volatility.

V. Conclusion

This study documents a general decline in the volatility of employment growth and examines some of its possible sources. A unique aspect of our analysis is the use of state-level panel data on employment growth during the period 1960 to 2002. Panel data allow a richer analysis than one based only on time series data [e.g., Stock and Watson (2002)]

[12] Eight percent is a conservative estimate of the lower bound because our procedure excludes the common effect of the federal funds rate on state-level volatility. The common effect is subsumed in the estimated time fixed effects, and is netted out when the lower bound is computed. Thus, the federal funds rate accounts for at least eight percent, but probably more. The same logic holds for each of the other aggregate variables as well.

or alternatively on cross-sectional data [e.g., Hammond and Thompson (2004).] Indeed, the decline in employment growth volatility was found to be widespread across states, albeit to differing degrees, suggesting a role for state-specific factors as well as common national influences.

Our analysis, which includes both state-specific and macroeconomic variables, indicates that, in fact, each of these factors plays a significant role in explaining fluctuations in employment growth volatility. The range of possible contributions of state-specific variables in the full sample was found to be less than that of the macro variables but nonetheless important. Among the aggregate factors separately identified, monetary policy, changes in the inventory-to-sales ratio, changes in the ratio of total trade to GDP, and oil prices significantly affected state-level volatility, although to differing degrees.

With regard to state-level factors, the share of state total employment in manufacturing and state banking deregulation each contributed significantly to fluctuations in volatility. These variables were found to matter even after controlling for state fixed effects and state-specific time trends. In sum these findings show that sub-national data can be important for understanding the variety of forces that buffet both state and national economies.

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Table 1: Structural Break Dates for State Volatility Series*

State	Break Date	Average Volatility - Pre-break	Average Volatility-Post-break	Percent Difference (Post vs. Pre)
AL	1983Q3	0.34	0.20	-0.42
AR	1984Q3	0.46	0.25	-0.45
AZ	1992Q4	0.65	0.29	-0.55
CA	1981Q3	0.36	0.27	-0.26
CO	1988Q2	0.54	0.25	-0.54
CT	1994Q1	0.43	0.24	-0.45
DE	1977Q1	0.78	0.43	-0.44
FL	1980Q3	0.57	0.29	-0.49
IA	1991Q3	0.41	0.16	-0.61
ID	1980Q1	0.62	0.44	-0.29
IL	1990Q3	0.35	0.17	-0.52
IN	1982Q1	0.58	0.28	-0.51
KS	1979Q2	0.52	0.27	-0.49
KY	1984Q3	0.53	0.21	-0.59
LA	1985Q2	0.59	0.39	-0.34
MD	1986Q4	0.42	0.29	-0.30
ME	1993Q1	0.45	0.26	-0.42
MI	1971Q1	1.12	0.45	-0.60
MN	1987Q1	0.34	0.17	-0.49
MO	1986Q3	0.32	0.18	-0.44
MS	1964Q2	0.58	0.33	-0.42
MT	1992Q1	0.66	0.38	-0.43
ND	1986Q4	0.67	0.32	-0.52
NE	1985Q4	0.44	0.25	-0.43
NH	1989Q2	0.48	0.41	-0.13
NM	1975Q3	0.61	0.33	-0.47
NV	1996Q4	0.70	0.24	-0.66
NY	1971Q2	0.25	0.34	0.34
OH	1988Q2	0.41	0.17	-0.59
OK	1986Q3	0.54	0.31	-0.42
OR	1983Q3	0.54	0.27	-0.50
PA	1964Q2	0.56	0.25	-0.55
RI	1991Q1	0.51	0.41	-0.21
SD	1992Q1	0.54	0.23	-0.57
TN	1982Q1	0.38	0.24	-0.36
TX	1979Q2	0.32	0.37	0.17
UT	1964Q1	0.50	0.43	-0.13
VA	1991Q3	0.33	0.21	-0.36
VT	1991Q3	0.49	0.23	-0.54
WA	1979Q2	0.62	0.33	-0.47
WI	1992Q2	0.32	0.14	-0.55
WV	1978Q2	0.79	0.61	-0.22
WY	1985Q3	0.95	0.58	-0.39

* Volatility in Georgia, Massachusetts, North Carolina, New Jersey, and South Carolina did not exhibit structural breaks.

Table 2: F Tests for the Estimated Coefficients[†]

Variable	F Test for Joint Significance	F Test for Equality of Coefficients
state dummies	4.89***	4.99***
time dummies	2.74***	2.72***
state-specific break dummies	5.80***	5.94***
state-specific time trends	2.70***	2.75***
state-specific time trends interacted with break	3.82***	3.59***
state-specific deregulation dummies	4.31***	4.36***
federal funds rate	2.01***	2.05***
federal funds rate interacted with break	4.10***	4.20***
Hamilton oil price index	2.27***	2.15***
Hamilton oil price index interacted with break	3.02***	3.09***
change in state-specific manufacturing shares	2.85***	2.69***
change in state-specific manufacturing shares interacted with break	6.34***	6.45***
change in ratio of total trade to GDP	1.77***	1.80***
change in total trade ratio interacted with break	4.19***	4.29***
change in inventory-to-sales ratio	1.82***	1.85***
change in inventory-to-sales ratio interacted with break	3.51***	3.55***

[†] *** indicate significance at the 1 percent levels.

Table 3: The Contribution of National vs. State-specific Variables to Employment Volatility

(1960:2 to 2002:4)

Panel A

Equation specification	R^2
Full equation	0.5666
Only state-specific variables[a]	0.2930
Only national variables[b]	0.4533

Panel B

Variables	Contribution to Volatility
State-specific Variables	11.3 percent to 29.3 percent
National Variables	27.4 percent to 45.3 percent

[a] The state-specific regression includes state fixed effects, break dummies, state-specific time trends, deregulation dummies, and manufacturing share of total state employment, both alone and multiplied by the state-specific break dummies.

[b] The national regression includes the time fixed effects and the interacted macro variables, both alone and multiplied by the state-specific break dummies.

Table 4: Accounting for Employment Volatility in the Full Sample
(1960:2 to 2002:4)

Equation specification[a]	Contribution to Volatility
State variables	
State fixed effects only	1.8 percent to 12.5 percent
State-specific time trends	1.2 percent to 11.8 percent
Deregulation	2.1 percent to 9.4 percent
Change in state manufacturing employment share	5.2 percent to 16.7 percent
National variables	
Time fixed effects only	3.3 percent to 13.3 percent
Federal funds rate	7.5 percent to 23.9 percent
Oil prices	5.3 percent to 13.5 percent
Change in inventory-to-sales ratio	5.5 percent to 11.0 percent
Change in ratio of total trade to GDP	2.1 percent to 7.2 percent

Figure 1: Average State Employment Growth Volatility

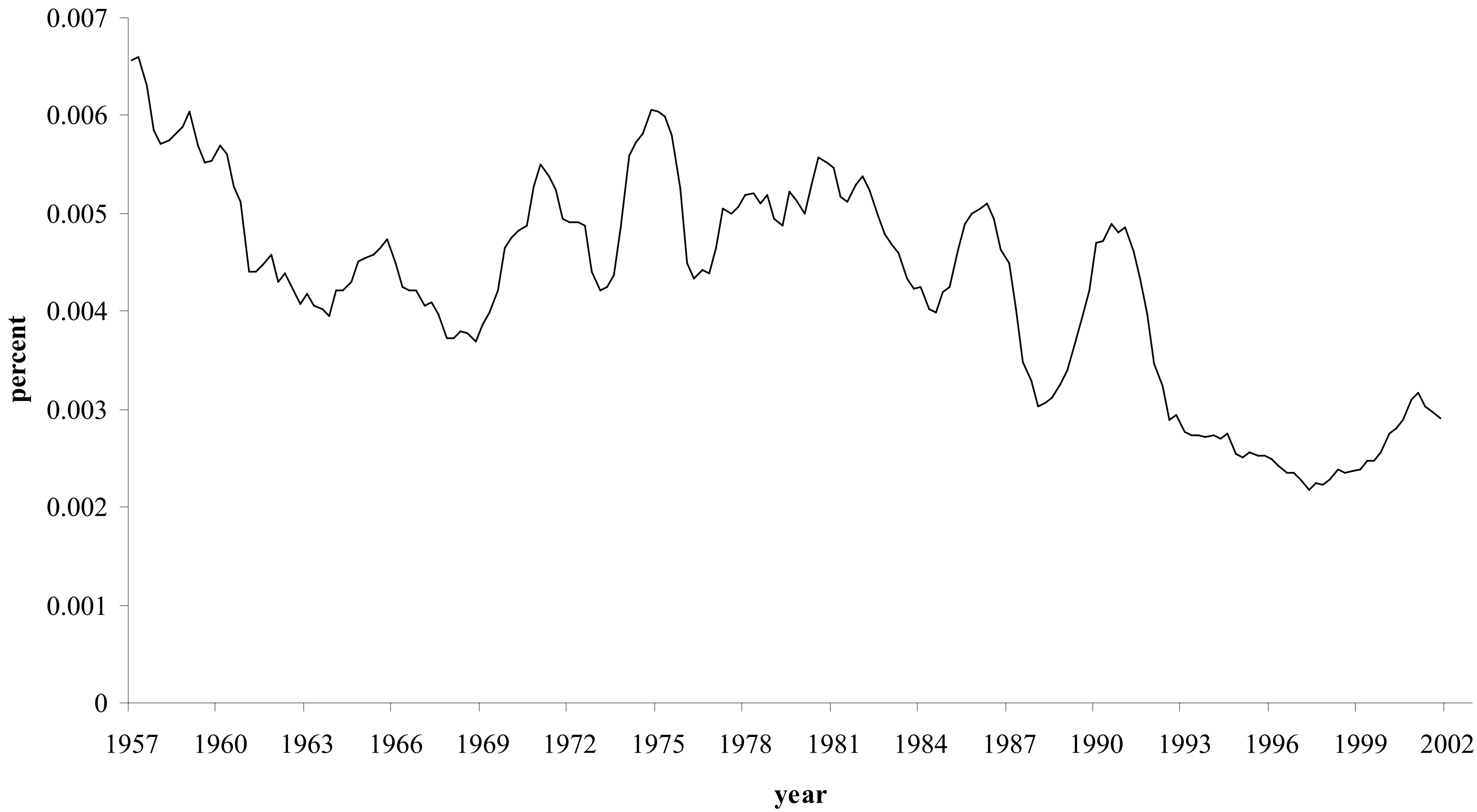

Figure 2: State Employment Growth Volatility Break Dates
(Andrews-Ploberger test)

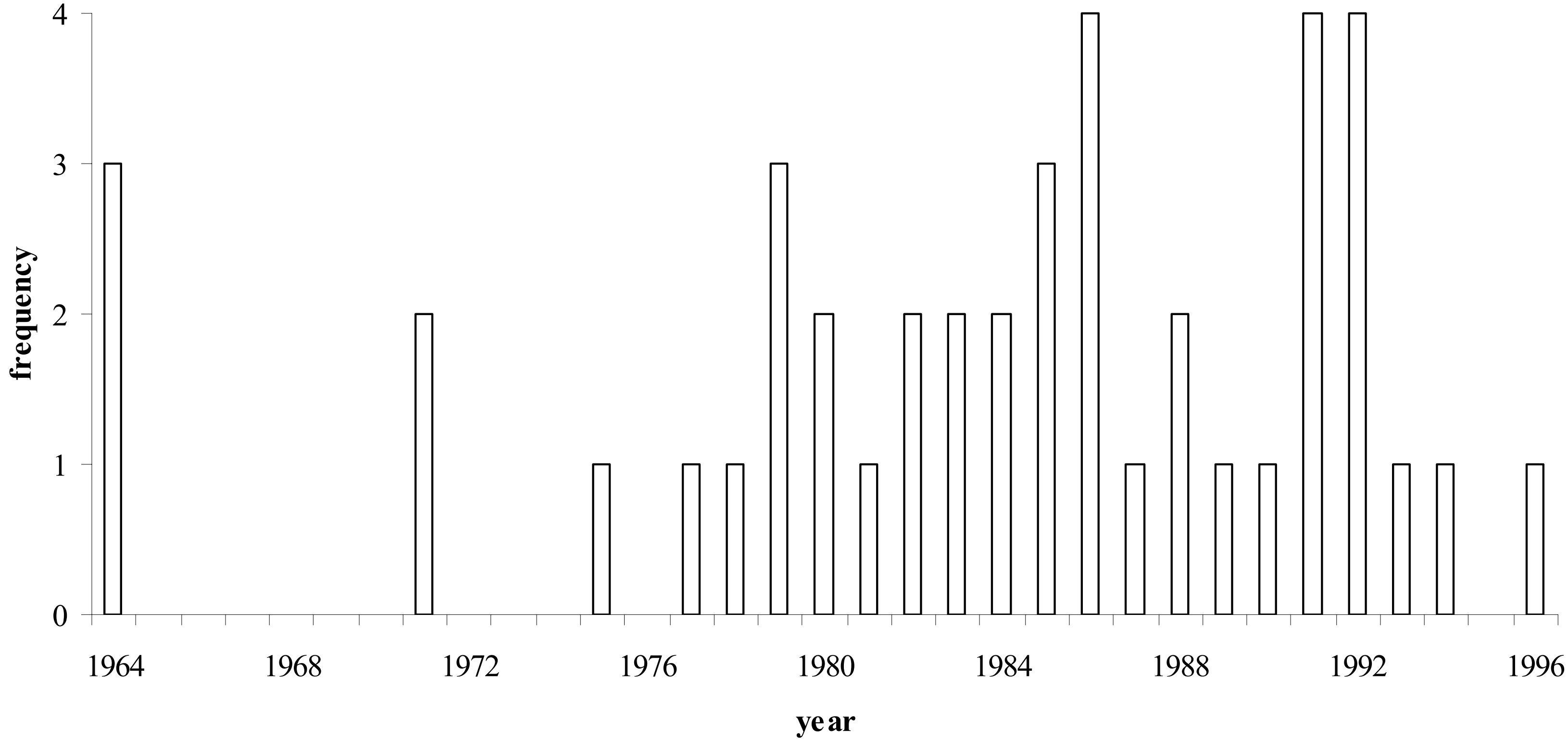

Figure 3: Kernel Density Estimates of Volatility Distributions

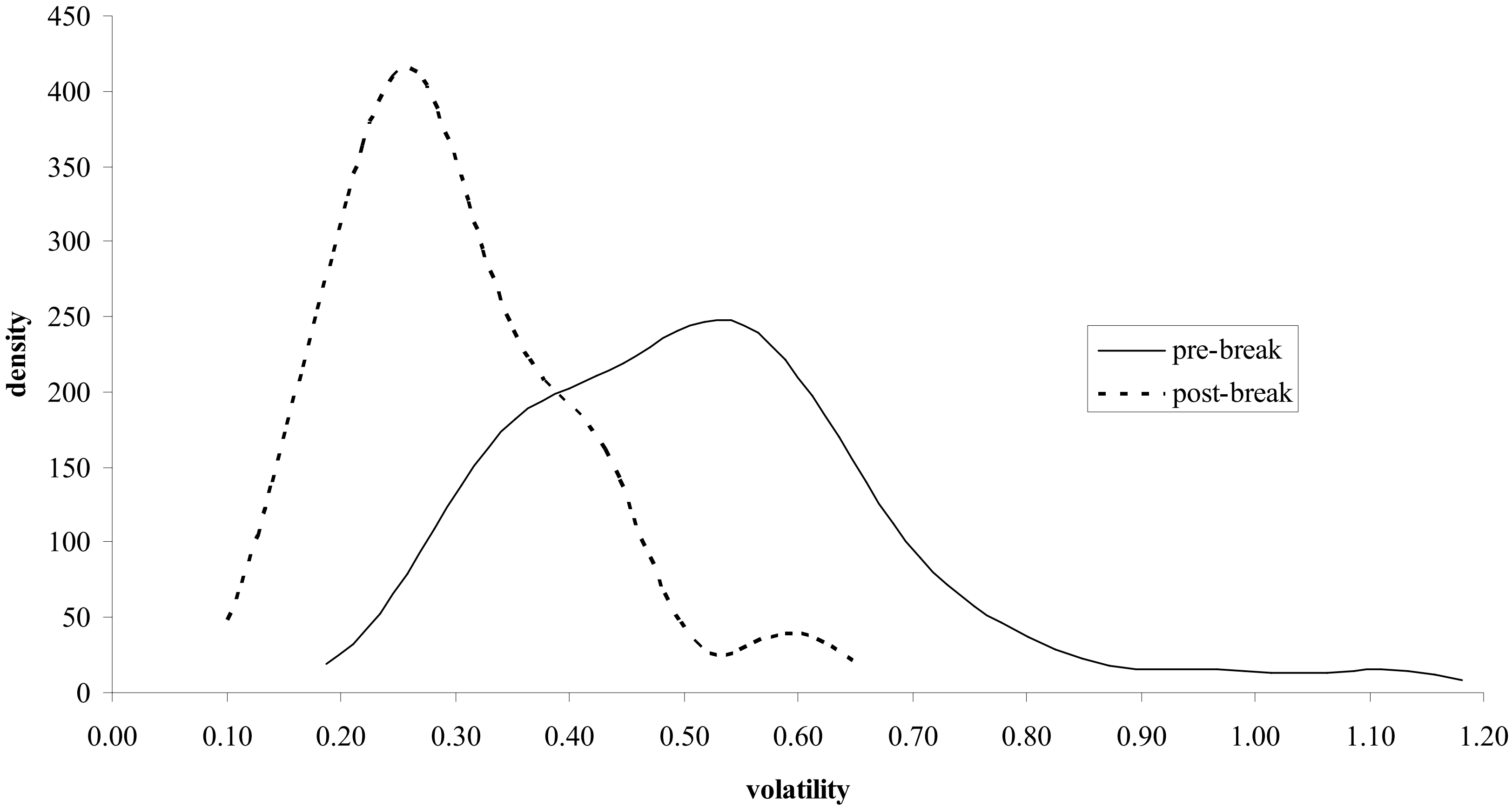

Figure 4: Federal Funds Rate

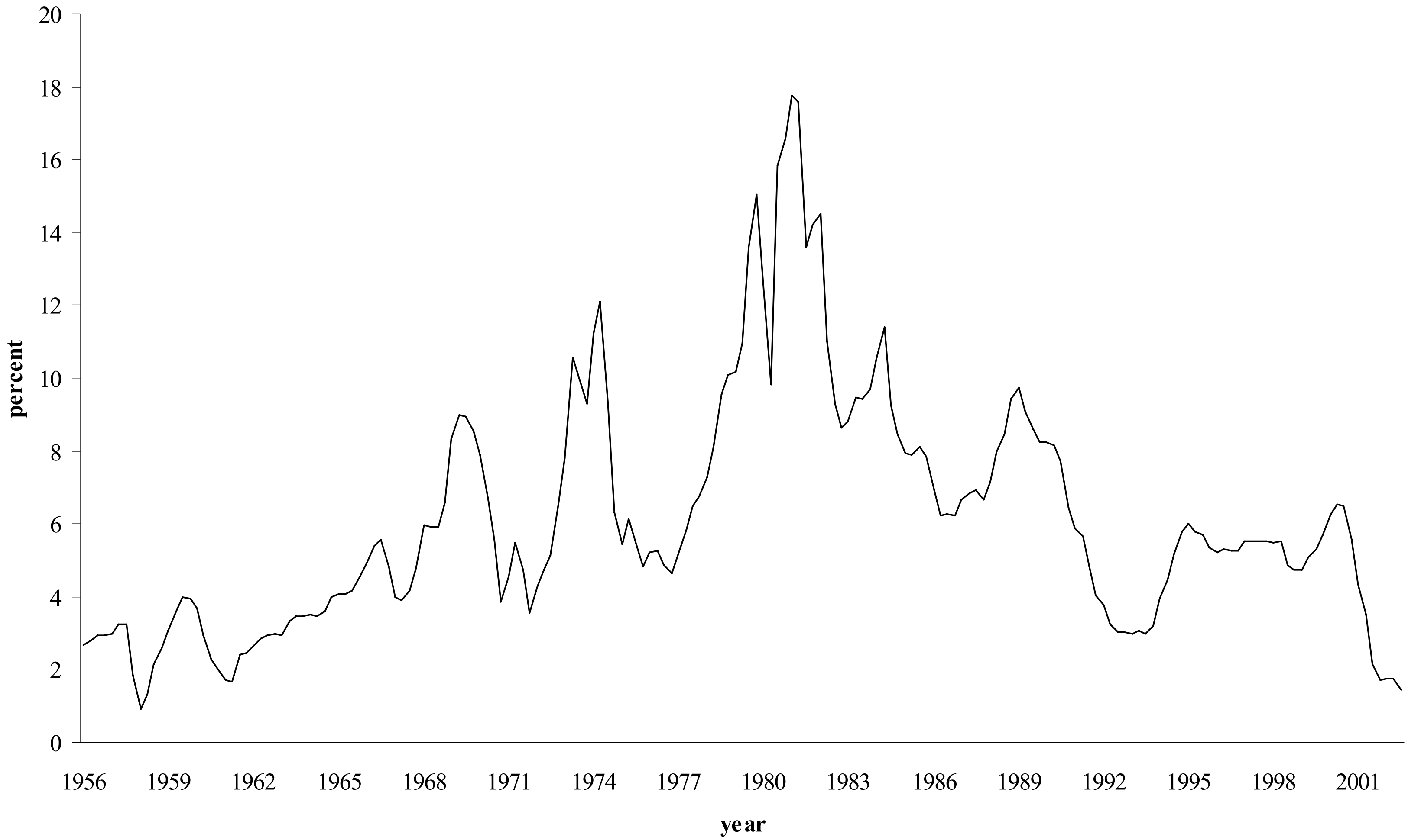

Figure 5: Hamilton Net Oil Price Increase

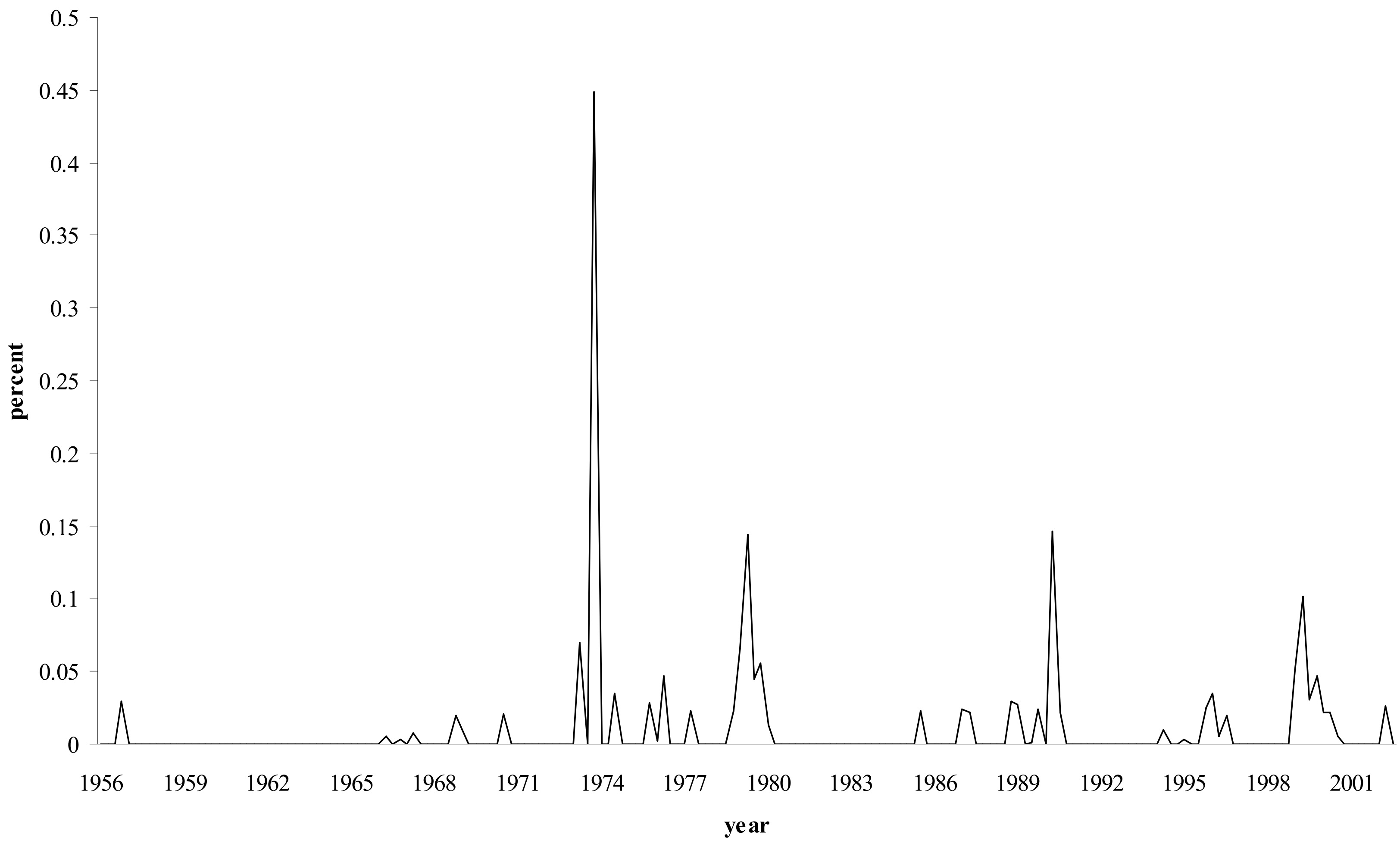

Figure 6: First Difference in Inventory-Sales Ratio

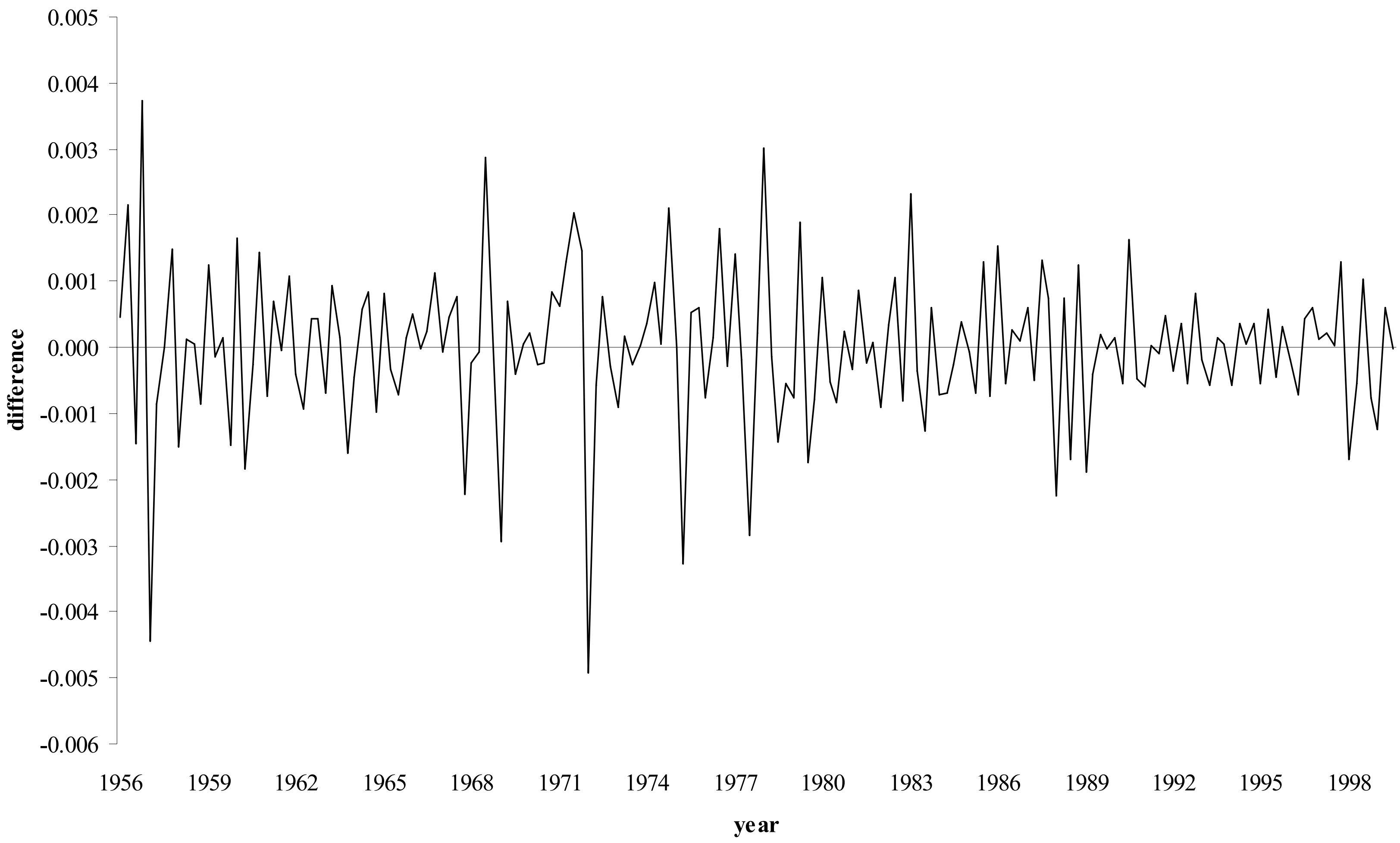

Figure 7: First Difference in Total Trade to GDP Ratio