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STATE EMPLOYMENT GROWTH VOLATILITY

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Abstract

This study documents a general decline in the volatility of employment growth during the period 1956 to 2005 and examines its possible sources. Estimates from a state-level pooled cross-section/time-series model indicate that aggregate and state-level factors each account for an important share of the total explained variation in state-level volatility. Specifically, state-level factors have contributed as much as 16 percent, while aggregate factors are found to account for up to 46 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. Aggregate factors that are quantitatively important in accounting for volatility include monetary policy, the state of the national business cycle, and oil-price shocks.

The Great Moderation is defined by a sharp drop in the volatility of most macroeconomic variables since the mid-1980s (e.g., Kim and Nelson, 1999, Stock and Watson, 2002, and McConnell and Perez-Quiros, 2000). The magnitude of the decline in volatility is substantial: For the nation, growth of output has been one-half and growth of employment two-thirds less volatile than they were in the 1960s and 1970s.

However, while the change in volatility between the pre- and post-1984 sub-periods was substantial, there were large movements in volatility within each of the two sub-periods as well. For example, we estimate that employment growth volatility decreased by around 80 percent between 1958 and 1964. Similarly, volatility grew by 450 percent from 1997 to 2002. We believe much is to be gained by studying the macroeconomic forces that have underpinned changes in employment growth volatility throughout the past 50 years.

While there is a large literature that examines the volatility pattern of aggregate economic variables and considers their determinants, there are few studies that use state-level data to better understand the factors driving fluctuations in volatility.[1] 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

[1]Recent studies that used state-level data to examine volatility include Carlino, DeFina, and Sill (2003), Anderson and Vahid (2003), Owyang, Piger, and Wall (2008), and Grennes, Guerron-Quintana, and Leblebicioğlu (2009).

account for up to 46 percent of the explained variation, while state-level factors have contributed as much as 16 percent. Among the aggregate factors separately identified, variation in monetary policy, oil price shocks, and a composite index of business cycle activity significantly affected state-level volatility, although to differing degrees. 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.

The addition of state-level data to the analysis of volatility provides a number of benefits compared to using aggregate data alone. A key benefit is the greater number of samples (48 for states compared with one in an aggregate study) and the corresponding additional dispersion that allows more precise estimation of factors thought to influence fluctuations in volatility. Another benefit is the mitigation 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 likely react to individual state-level developments, the issue of endogeneity is much less of a concern in a state-level analysis of volatility. In regression studies of aggregate volatility, unobserved heterogeneity across states that affects volatility will be subsumed in the regression error term. This unobserved state heterogeneity would 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 financial 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. 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 and 1999).

1. LITERATURE REVIEW

Numerous papers have examined the existence and causes of a one-time decrease in economic volatility that purportedly occurred in the mid-1980s. At the macro level, relevant studies include Blanchard and Simon (2001), Clarida, Gali, and Gertler (2000), Orphanides (2001), McConnell and Perez-Quiros (2000), Stock and Watson (2002), Kim and Nelson (1999), Gordon (2005), and Leduc and Sill (2007). These studies have explored the possible contributions of improved monetary policy, structural changes such as de-industrialization and improved inventory control, and good luck in the form of smaller shocks to the economy. A related strand of literature has examined similar phenomena using state-level data (Carlino, DeFina, and Sill, 2003, Anderson and Vahid, 2003, Owyang, Piger and Wall, 2008 and Grennes, Guerron-Quintana, and Leblebicioğlu, 2009). These papers tend to find substantial heterogeneity in state volatility.

Alternatively, other researchers have used cross-sectional data for states and metropolitan areas to analyze the role of industrial diversification on cross-sectional differences in output and employment stability and instability. These studies typically focus on the average unconditional volatility of a variable's quarterly or annual growth over some single period (e.g., 1970 to 1990). The findings of these studies are somewhat mixed, but the bulk of the evidence indicates that more industrially diverse locations tend to be associated with lower employment volatility (Siegel, 1966, Conroy, 1975, Kort, 1981, Malizia and Ke, 1993, and Sherwood-Call, 1990).[2] Some studies, however, find no evidence favoring the diversity-stability view (Jackson, 1984, using multicounty aggregates for Illinois, and Attaran, 1986, for all states).

2. MEASURING STATE-LEVEL EMPLOYMENT GROWTH VOLATILITY

We focus on employment growth because it is a widely used indicator of real activity at the state level, 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, and only on an annual basis. State personal income data exist for the entire period of our study but only in nominal terms.

We measure state-level volatility using an approach similar to that in Morgan, Rime, and Strahan (2004). Specifically, the quarterly growth rate of state employment (measured as log differences) is regressed on state dummies (a_i) for the period 1956:3 to 2005:2:

[2] Using time series data for U.S. states, Anderson and Vahid (2003) and Grennes, Guerron-Quintana, and Leblebicioğlu (2009) find that reductions in income growth volatility are associated with greater industrial diversification.

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

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

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

which is measured as the deviation of employment growth in a given state-quarter from the average growth for a given state.[3] The data are seasonally adjusted quarterly nonagricultural payroll employment from the Bureau of Labor Statistics (BLS). The estimated equation has an adjusted R^2 of 0.0671. *F*-tests indicate both that the state fixed effects 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.[4] As can be seen, average employment growth volatility exhibited a general downward trend over time. A simple regression of the smoothed volatility on time produces a negative and highly significant coefficient. Despite the general declining trend in average state employment growth volatility, there is considerable time variation in volatility around the trend, with volatility increasing dramatically in periods of recession (e.g., the early years of 2000).

Similarly, the data reveal considerable variation across states. Figure 2 displays kernel density estimates of the frequency distribution for the average state-level volatilities.[5] The distribution generally has a normal shape with an elongated right tail

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[3] Alternatively, other researchers have computed volatilities using rolling standard errors or regression standard errors from rolling AR(1) models (e.g., Blanchard and Simon, 2001). However, the use of rolling standard errors complicates the panel estimation because it induces serial correlation in the data series.
[4] The volatility series shown in Figure 1 is constructed as the employment-weighted average of state volatilities, allowing the weights to change each quarter. The volatility series is smoothed using a one-sided four-quarter moving average.
[5] Given a kernel K(u), the estimated density function for x is:

indicating a few states with especially large volatilities. Table 1 contains details on the levels and trends of the average volatility for individual states. Regarding the levels of volatility, the cross-state mean is 0.571 with a minimum of 0.425 in New York and a maximum of 0.859 in Michigan. Four states (Michigan, Wyoming, West Virginia, Nevada, and Arizona) have average volatilities in excess of 0.7. Consistent with the cross-state average data, the volatility in each individual state has a downward trend during our sample period, with all but Wyoming's highly significant.

It has become popular to analyze volatility by focusing on the post-1984 years associated with the Great Moderation. Studies have, for example, searched for trend breaks and have sought to identify the sources of the shift in volatility between the pre- and post-break periods. Nevertheless, as seen in Figure 1, employment growth volatility fluctuates widely throughout the sample period, including within the time spans researchers identify as being pre- and post-break. While volatility fell 75 percent between 1983 and 1997, it also fell 80 percent between 1958 and 1964. Similarly, Figure 1 shows that there are other periods in which volatility increased substantially. This intra-period variation in employment growth volatility is potentially helpful to analyses of the sources of fluctuations in volatility (e.g., Owyang, Piger, and Wall, 2008, and Grennes, Guerron-Quintana, Leblebicioğlu, 2009).

3. SOURCES OF STATE-LEVEL EMPLOYMENT GROWTH VOLATILITY

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

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 Xi. The estimates use the Gaussian kernel and an optimal bandwidth that minimizes the mean integrated square error. Should we say what h is?

Having documented the substantial and disparate declines in state employment growth volatility, this section turns to an examination of the possible sources. The fact that most states experienced volatility declines during the 1956-2005 sample period suggests that part of the variance might be due to common state responses to aggregate shocks. A pooled cross-section/time-series, or panel model, is useful in studying the determinants of changes in volatility. In the framework of a panel, time fixed effects account for the impacts of aggregate forces that vary over time but not across states and, as such, constitute purely macro influences.

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. Another advantage of a panel model is that it allows states to respond differently to common national shocks. It's also likely 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.

Over time, states can also undergo unique changes 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).[6] Similarly, as noted by Anderson and Vahid (2003) and Grennes, Guerron-Quintana, and Leblebicioğlu (2009), state-specific changes in industrial structure can potentially alter the time series profile of a state's employment growth volatility.

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 that occurred during the Great Moderation 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' different responses to aggregate shocks, as well as state-specific forces. The next section develops an empirical approach designed to capture these broad determinants of volatility.

[6] 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 them approving legislation to allow deregulation between 1985 and 1988. With the exception of Hawaii, all states allowed interstate banking by 1993.

4. 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.[7]

Empirical Specification

The sample consists of quarterly data covering the period of 1956 to 2002.[8] The sample contains 8,976 observations: 187 quarters of data for 48 states. Contemporaneous and lagged values of each explanatory variable are used to allow for delayed or persistent impacts.

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

$$\left|\varepsilon_{it}\right| = \alpha_0 + \alpha_i + \alpha_t + \beta_i t_i + \gamma_t t + \delta_i dreg_{i,t} + \phi_i \, \dot{manshare}_i + \sum_{m=1}^{3}(\varphi_{i,m} * Macro_{m,t}) + \nu_{it} \qquad (3)$$

where: $\left|\varepsilon_{it}\right|$ is the absolute value of quarterly employment growth fluctuations, measured as in equation (2);[9] t indexes time (quarters), i indexes the 48 states, and m indexes the subset of aggregate explanatory variables to be estimated; α_i is a dummy variable equal to 1 for state i and 0 otherwise (state fixed-effect) ; α_t is a quarterly time dummy (time fixed-effect); t is an aggregate time trend (common to all states) t_i is a time trend for state i (captures state deviations from the aggregate time trend); $dreg_{i,t}$ is the deregulation

[7]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.

[8] The Bureau of Labor Statistics reported employment using the SIC classification until 2002 and on a NAICS basis thereafter. Since there is no comprehensive concordance between SIC and NAICS, we only use data through 2002 for consistency.

[9] Alternatively, volatility could be measured using 20-quarter rolling standard errors, as others have done (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. This would limit the panel to eight separate periods, which would be insufficient for the analysis undertaken in this paper.

dummy for state i; $\dot{manshare}$ is the growth in the state manufacturing employment share; and, $Macro_{m,t}$ is the m^{th} aggregate variable that is interacted with the state fixed-effects.

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. A disadvantage is that once the model includes time fixed effects, no other purely macro variables can be entered because they will be co-linear with the time fixed effects. However, studies have singled out certain aggregate variables (such as changes in monetary policy and oil price shocks) as such important determinants of volatility that they will be interacted with our state fixed-effects variables to allow states to respond differentially to these aggregate variables. The macroeconomic literature has a longstanding interest in variations in monetary policy and oil price shocks in general and special attention has been accorded to these variables in the recent literature seeking to explain swings in volatility (Clarida, Gali, and Gertler, 2000, Orphanides, 2001, Leduc, Sill, and Stark, 2007, Stock and Watson, 2002, Leduc and Sill, 2007, and Hamilton, 1983, 1996, and 2003). In addition to these variables we gauge the state of the aggregate business cycle using a coincident index developed in Aruoba, Diebold, and Scotti (2008), hereafter ADS. The ADS index will be interacted with the state fixed effects to allow for idiosyncratic state level response to aggregate business cycle conditions.

We operationalize these aggregate variables as follows. Monetary policy shocks are measured using the general strategy of Christiano, Eichenbaum, and Evans (1998). That is, we estimate a small VAR (described below) in which the federal funds rate is included as a policy instrument. The structural errors from the federal funds rate equation are interpreted as shocks to monetary policy. We then measure changes in monetary policy that are potential sources of more general economic volatility using the squared structural residuals. The idea is that shifts in monetary policy manifest themselves as changes in the volatility of policy shocks. To measure structural monetary policy shocks we employ a two-variable VAR that includes four lags of both the federal funds rate and the composite index of business cycle activity developed by ADS. A recursive identification scheme is used with the ADS index ordered first. Consequently, aggregate activity (the slow moving variable) is assumed not to respond to monetary policy shocks within quarter, while monetary policy (the fast moving variable) responds to the aggregate within quarter. Our measured monetary policy variable is shown in Figure 3.

The state of the aggregate business cycle is proxied using the level of the ADS index. The ADS index is designed to track real macroeconomic activity at high frequency and has zero mean so that progressively more negative (positive) values indicate progressively weaker (stronger) business conditions. Its underlying economic indicators include weekly initial jobless claims, monthly payroll employment, industrial production, personal income less transfer payments, manufacturing and trade sales, and quarterly real GDP, and mix high- and low-frequency information and stock and flow dynamics. For this analysis, we aggregate the weekly ADS index into quarterly values. The index is plotted in Figure 4.

The oil price shock at time *t* is measured as the net oil price increase over the previous 12 months (Hamilton, 2003). 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 demonstrates a more stable link to real activity than does the actual price of crude oil over the postwar sample. The oil price variable is shown in Figure 5.

Concerning state-level controls, state fixed effects are used to account for time invariant idiosyncratic state-level factors that can influence state volatility. Similarly, 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).

Another potentially important influence on state-level volatility is a change in a state's industrial structure (Anderson and Vahid, 2003, and Grennes, Guerron-Quintana, Leblebicioğlu, 2009). We capture this possibility using the change in a state's manufacturing employment share. Finally, the model includes state-specific time trends to capture state factors that change gradually over time, such as demographic shifts in state populations.

Estimation and Results

Prior to estimation, the variables in equation (3) were checked for non-stationarity using the Im, Peseran, and Shin (2003) panel unit root test, which allows the unit root process to differ across states. The null of non-stationarity can be rejected for employment growth volatility but not for state manufacturing employment share. Non-stationarity can be easily rejected for the growth rate of the manufacturing share, and the latter variable is used in the regression analysis. Since all three macro variables are stationary by construction, they can be used in their original level form in the estimations. Still, to be on the safe side, we conducted standard ADF tests for each of these variables using a trend and six lags. The null of a unit root process is easily rejected in each case ($p < 0.000$).

Estimated coefficients for equation (3) are obtained using a Newey-West heteroskedasticity- and autocorrelation-consistent estimator. A series of regressions were run to determine the appropriate lag length for each macro variable.[10] Based on the results from these regressions, four lags of the oil price variable, six lags of the monetary policy variable, and three lags of the economic activity index are used, along with their contemporaneous values.

Estimation of equation (3) produced an $R^2 = 0.4944$. 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 of the state-level variables is found to be jointly significant at the 1 percent level, with the exception of the change in the manufacturing share of employment, which is significant at the 10 percent level. Similarly, *F*-tests for the equality of coefficients are rejected for each variable in the model. These findings

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

suggest that state-level influences are important factors determining volatility. The tests are also informative for deregulation and manufacturing shares. The joint significance of the deregulation dummies (F = 116.4) 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 restricted deregulation to have the same effect on each state. As already indicated, our results show that these restrictions are perhaps too strict. An F-test of the null hypothesis of the equality of 48 estimated coefficients on the deregulation variable is soundly rejected (F = 115.0).

The finding that the change in the manufacturing share has a negative and significant effect on volatility is consistent with previous findings based on state-level data (Anderson and Vahid, 2003, and Grennes, Guerron-Quintana, and Leblebicioğlu, 2009). 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 (such as the Great Moderation), they do appear to have contributed to the longer run, more continuous, volatility changes examined in this study.

The results also offer support for an influence of aggregate variables on state-level volatility. 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, and changes in the ADS index have all had differential effects on state-level volatility. Importantly, these aggregate variables matter even when all are simultaneously considered.

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' different 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 explanatory variables account for?

Accounting for Volatility

We parse out contributions to volatility using auxiliary regressions, which are then used to generate bounds on the size of the contributions of each variable or subset of variables. First, we re-estimate equation (3) using only the macro or aggregate factors as regressors:

$$|\varepsilon_{it}| = \alpha_0 + \alpha_t + \gamma_t t_i + \sum_{m=1}^{3}(\varphi_{i,m} * Macro_{m,t}) + \nu_{it} \qquad (4)$$

The R^2 from this regression gives the upper bound for the contribution of the macro factors, since all co-variance between them and the excluded aggregate variables is allocated to the macro factors. We refer to the R^2 from Equation (4) as R_M^2. Similarly, a second auxiliary regression that includes only the state-specific variables maximizes the measured contribution of these variables since all co-variance with the now excluded macro factors is ascribed to them. The R^2 from this equation is called R_S^2.

Panel A of Table 3 presents the goodness of fit statistics for the three models estimated thus far. Panel A of the table presents the R^2 for the full equation (call this R_{ALL}^2), and the R^2s for the equations that contain only macro variables and only the state-specific variables, respectively. R^2_{ALL} indicates that the full model explains 49 percent of the total variation in state-level employment volatility. The R^2_S for the state-specific variables indicates that these variables explain *at most* 16 percent of the variation in employment growth volatility. The R^2_M for the macro variables indicates that these variables alone explain at most 46 percent of the variation.

The various R^2 given in Table 3 separately represent the maximum contributions for either the macro variable taken together or for the state variables as a group. We can also generate lower bound estimates for the contribution both of the state and macro variables. An estimate of the lower bound for the contribution of macro factors is obtained by subtracting R^2_S from the R^2 of the full equation, R^2_{ALL}. We refer to this lower bound estimate for macro variables as R^2_{LM} (i.e., $R^2_{LM} = R^2_{ALL} - R^2_S$). An analogous exercise is conducted to get the lower bound for the contribution of the state-specific variables, R^2_{LS} (i.e., $R^2_{LS} = R^2_{ALL} - R^2_M$).

Panel B of Table 3 presents estimates of the combined effects of the macro variables versus the combined effects of state-level variables. As can be seen, the range of contributions for the macroeconomic variables is between 34 percent and 46 percent of the total variation in employment growth volatility. The range of potential contributions from the state-specific factors is 4 percent to 16 percent. 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 to be important. State-specific factors account for between about 8 percent of the total explained variation in volatility (3.8 percent/49 percent) to around 33 percent.

We also isolate the contribution of five individual variables (variance in monetary policy, oil price shocks, the ADS index, financial deregulation, and changing share of manufacturing employment) in the same way as we did for the groups of macro. For example, to isolate the effects of monetary policy, we first re-estimate equation (3) but with only the monetary policy variable included in the regression:

$$\left|\varepsilon_{it}\right| = \alpha_0 + \sum_{j=0}^{6} \xi_{t-j} * Monpol_{t-j} + \sum_{j=0}^{6} (\varphi_{i,t-j} * Monpol_{t-j}) + \nu_{it} \tag{4}$$

where *Monpol* refers to the monetary policy variable. The first summation on the right-hand side of equation (4) gives the common (across states) aggregate effect of the variance of monetary policy. The second summation gives the state-specific responses to the variance of policy. The R^2 from this regression gives the upper bound for the contribution of monetary policy, since all co-variance between policy and the excluded variables is allocated to monetary policy. We refer to the R^2 from the estimation of equation (4) as R_P^2 .

An estimate of the lower bound for the contribution of monetary policy is generated by estimating a second auxiliary regression that includes all the variables except for monetary policy. The R^2 from this equation, called R_{NP}^2 , maximizes the measured contribution of the non-monetary-policy variables since all co-variance with the now excluded policy variable is ascribed to the other variables. Thus, subtracting R_{NP}^2 from R_{ALL}^2 yields the lower bound for monetary policy. That is, the lower bound estimate, R_L^2, is defined as $R_L^2 = R_{ALL}^2 - R_{NP}^2$. This procedure was likewise followed to obtain estimates of the ranges of contributions for oil prices, the ADS index, financial deregulation and the growth in the manufacturing employment share.

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 5 percent and 15 percent of the variation. The upper end of the range for monetary policy is similar to the estimated explanatory power of monetary policy found by Leduc and Sill (2007) when examining the post-1984 decline in GDP volatility. Oil prices explain around 4 percent to 8 percent, while the aggregate activity index explains around 3 percent to 6 percent.

The results show that each of the state-level variables has played a role in explaining volatility. The change in states' manufacturing shares explains at most only about 3 percent, while deregulation of interstate banking could explain an additional 7 percent. The results once again suggest the importance of incorporating state-level factors into an analysis of volatility.

5. CONCLUSION

We document a general decline in the volatility of employment growth and examine some of its possible sources. A unique aspect of our analysis is the use of state-level panel data on employment growth from 1956 to 2002. Panel data allow a richer analysis than one based only on time series data (e.g., Stock and Watson, 2002) 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 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.

REFERENCES

Anderson, Heather, and Farshid Vahid. (2003) "The Decline in Income Growth Volatility in the United States: Evidence from Regional Data, Monash University Working Paper 21.

Aruoba, S. Boragan, Francis X. Diebold, and Chiara Scotti. (2008) "Real-Time Measurement of Business Conditions," Federal Reserve Bank of Philadelphia Working Paper 08-19.

Attaran, Moshen. (1986). "Industrial Diversity and Economic Performance in U.S. Areas," *Annals of Regional Science*, 20, 44-54.

Blanchard, Olivier, and John Simon. (2001) "The Long and Large Decline in U.S. Output Volatility," *Brookings Papers on Economic Activity,* 135-164.

Carlino, Gerald A., and Robert DeFina. (1998) "The Differential Regional Effects of Monetary Policy," *Review of Economics and Statistics* 80, 572-87.

Carlino, Gerald A., and R. DeFina. (1999) "The Differential Regional Effects of Monetary Policy: Evidence from the U.S. States, *Journal of Regional Science* 39, 229-358.

Carlino, Gerald A., R. DeFina, and Keith Sill. (2003) "Postwar Period Changes in Employment Volatility: New Evidence from State/Industry Panel Data," Federal Reserve Bank of Philadelphia Working Paper 03-18.

Christiano, Lawrence J., Martin Eichenbaum, and Charles L. Evans. (1999) "Monetary Policy Shocks: What Have We Learned, and To What End," with Martin Eichenbaum and Charles Evans, in Taylor and Woodford, eds., *Handbook of Monetary Economics*.

Clarida, Richard, Jordi Gali, and Mark Gertler. (2000) "Monetary Policy Rules and Macroeconomic Stability: Evidence and Some Theory," *Quarterly Journal of Economics*, 115, 147-80.

Conroy, Michael E. (1975) "The Concept and Measurement of Regional Industrial Diversification," *Southern Economic Journal*, 41, 492-505.

Gordon, Robert J. (2005) "What Caused the Decline in U.S. Business Cycle Volatility?" National Bureau of Economic Research Working Paper 11777.

Grennes, Thomas, Pablo Guerron-Quintana, and Asli Leblebicioğlu. (2009) "Economic Development and Heterogeneity in the Great Moderation Among the States, Unpublished manuscript.

Hamilton, James D. (1993) “Oil and the Macroeconomy,” *Journal of Political Economy* 91, 228-48.

Hamilton, James D. (1996) “This Is What Happened to the Oil Price-Macroeconomy Relationship,” *Journal of Monetary Economics*, 38, 215-20.

Hamilton, James D. (2003) “What Is an Oil Shock?” *Journal of Econometrics,*113, 363-98.

Hammond G. W., and E. Thompson. (2004) “Employment Risk in U.S. Metropolitan and Nonmetropolitan Regions: The Influence of Industrial Specialization and Population Characteristics,” *Journal of Regional Science* 44, 517-42.

Im, Kyung So, Pesaran, M. Hashem, and Shin, Yongcheol. (2003) “Testing for Unit Roots in Heterogeneous Panels,” *Journal of Econometrics*, 115, 53-74.

Jackson, Randall W. (1984) “An Evaluation of Alternative Measures of Regional Industrial Diversification,” *Regional Studies*, 18, 103-112.

Kahn, James, Margaret McConnell, and Gabriel Perez-Quiros. (2002) “On the Causes of the Increased Stability of the U.S. Economy,” Federal Reserve Bank of New York *Economic Policy Review*, 183-202.

Kim, Chang-Jin, and Charles Nelson. (1999) “Has the U.S. Economy Become More Stable? A Bayesian Approach Based on a Markov-Switching Model of the Business Cycle,” *Review of Economics and Statistics* 81, 608-16.

Kort, John R. (1981) “Regional Economic Instability and Industrial Diversification in the U.S.,” *Land Economics*, 57, 596-608.

Leduc, Sylvain, and Keith Sill. (2007) “Monetary Policy, Oil Shocks, and TFP: Accounting for the Decline in U.S. Volatility,” forthcoming, *Review of Economic Dynamics*.

Leduc, Sylvain, Keith Sill, and Thomas Stark. “Self-Fulfilling Expectations and the Inflation of the 1970s: Evidence from the Livingston Survey,” (2007) forthcoming, *Journal of Monetary Economics*.

Malizia, Emil E., and Shanzi Ke. (1993) “The Influence of Economic Diversity on Unemployment and Stability,” *Journal of Regional Science*, 33, 221-235.

McConnell, M, and G. Perez-Quiros. (2000) “Output Fluctuations in the United States: What Has Changed Since the Early 1980s?” *American Economic Review*, 90, 1464-76.

Morgan, Donald, Bertrand Rime, and Philip Strahan. (2004) “Bank Integration and State Business Cycles,” *Quarterly Journal of Economics,* 1555-84.

Orphanides, Athanasios. (2001) “Monetary Policy Rules, Macroeconomic Stability, and Inflation: A View from the Trenches,” manuscript, Board of Governors of the Federal Reserve System.

Owyang, Michael, Jeremy Piger, and Howard Wall. (2008) “A State-Level Analysis of the Great Moderation,” unpublished manuscript, Federal Reserve Bank of St. Louis.

Sherwood-Call, Carolyn. (1990) “Assessing Regional Economic Stability: A Portfolio Approach,” *Economic Review*, Federal Reserve Bank of San Francisco (Winter), 17-26.

Siegel, Richard A. (1966) “Do Business Cycles Exist?” *Western Economic Journal*, 5, 44-57.

Stock, James, and Mark Watson. (2002) “Has the Business Cycle Changed and Why?” National Bureau of Economic Research Working Paper 9127 (August).

Table 1: Average State Volatilities and Volatility Trends
(1956:2 to 2004:4)

State	Volatility[a]	Trend[b]		State	Volatility[a]	Trend[b]
AL	0.49802	-0.00244		NC	0.53025	-0.00198
AR	0.53859	-0.00208		ND	0.52111	-0.00234
AZ	0.71098	-0.00077		NE	0.44361	-0.00265
CA	0.49827	-0.00223		NH	0.68634	-0.00089
CO	0.53919	-0.00189		NJ	0.43873	-0.00275
CT	0.56612	-0.00191		NM	0.48175	-0.00242
DE	0.65393	-0.00146		NV	0.71888	-0.00070
FL	0.55893	-0.00183		NY	0.42466	-0.00284
GA	0.54270	-0.00183		OH	0.60275	-0.00212
IA	0.52462	-0.00222		OK	0.54294	-0.00198
ID	0.60956	-0.00173		OR	0.62369	-0.00153
IL	0.50458	-0.00248		PA	0.48945	-0.00293
IN	0.69424	-0.00143		RI	0.63446	-0.00162
KS	0.53205	-0.00221		SC	0.56130	-0.00173
KY	0.58310	-0.00203		SD	0.50961	-0.00224
LA	0.59346	-0.0018		TN	0.54468	-0.00203
MA	0.56210	-0.00186		TX	0.49588	-0.00223
MD	0.51020	-0.00232		UT	0.54198	-0.00198
ME	0.57890	-0.00175		VA	0.46115	-0.00238
MI	0.85896	-0.00084		VT	0.57681	-0.00185
MN	0.47601	-0.00268		WA	0.59701	-0.00179
MO	0.47987	-0.00254		WI	0.48124	-0.00262
MS	0.59231	-0.00152		WV	0.82568	-0.00064
MT	0.63037	-0.00168		WY	0.83236	-0.00034

[a]Weighted average using employment in each year.
[b]State volatility trends estimated using a weighted OLS regression of volatility on state-specific time trends. Weights are state employment levels.

Table 2: F Tests for the Estimated Coefficients†

Variable	F Test for Joint Significance	F Test for Equality of Coefficients
State dummies	100.0***	98.8***
Time dummies	1685.4***	1708.4***
State-specific time trends	96.4***	94.5***
State-specific deregulation dummies	116.4***	115.0***
Change in manufacturing share	3.70*	na
Monetary policy variance	194.5***	202.6***
Hamilton oil price index	247.1***	251.3***
Aggregate activity index	72.5***	73.4***

† *, ** and *** indicate significance at the 10, 5 and 1 percent levels, respectively.

Table 3: The Contribution of National vs. State-Specific Variables to Employment Volatility
(1956:3 to 2002:4)

Panel A

Equation specification	R^2
Full equation	0.4944
Only national variables[a]	0.4561
Only state-specific variables[b]	0.1567

Panel B

Variables	Contribution to Volatility
National Variables	33.8 percent to 45.6 percent
State-specific Variables	3.8 percent to 15.7 percent

[a] The national regression includes the time fixed effects, an aggregate time trend, and the interacted macro variables.

[b] The state-specific regression includes state fixed effects, state-specific time trends, deregulation dummies, and manufacturing share of total state employment.

Table 4: Accounting for Employment Volatility in the Full Sample

(1956:2 to 2002:4)

Equation Specification[a]	Contribution to Volatility
National variables	
Monetary Policy Variance	5.3 percent to 14.9 percent
Oil prices	3.8 percent to 8.3 percent
Aggregate Activity Index	2.7 percent to 5.5 percent
State variables	
Deregulation	1.6 percent to 6.5 percent
Manufacturing employment share	1.1 percent to 2.5 percent

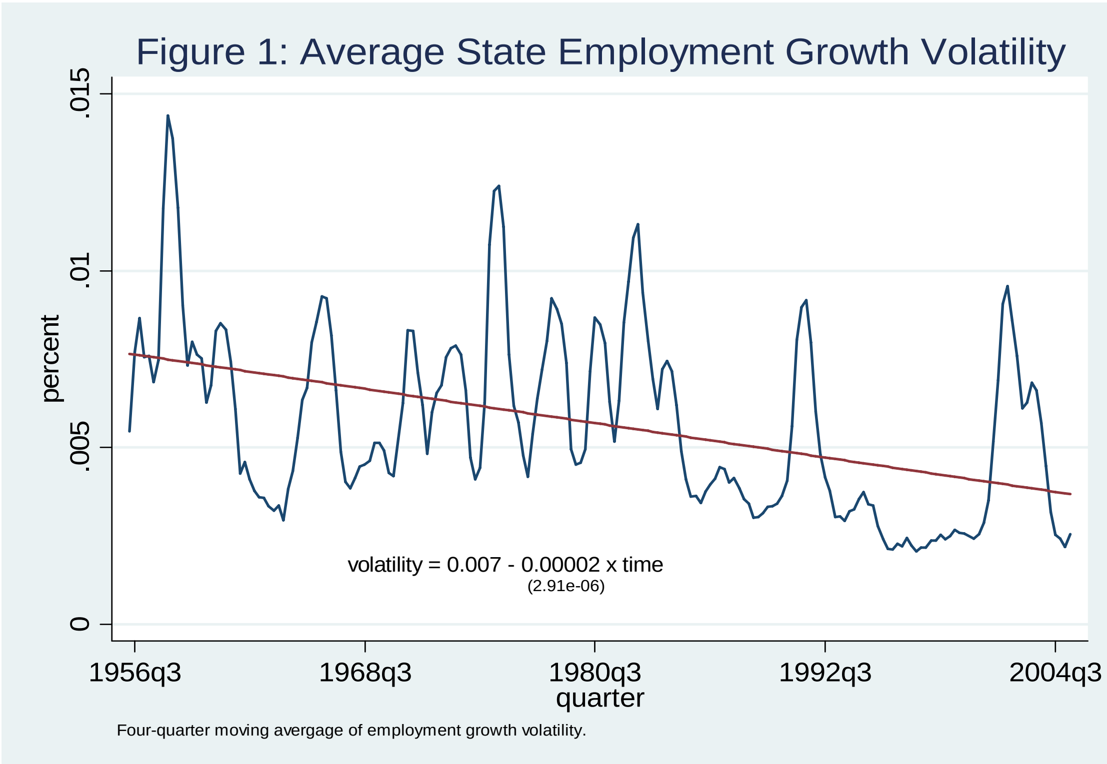
Figure 1: Average State Employment Growth Volatility
percent
.015
.01
.005
0
volatility = 0.007 - 0.00002 x time
(2.91e-06)
1956q3
1968q3
1980q3
1992q3
2004q3
quarter
Four-quarter moving avergage of employment growth volatility.

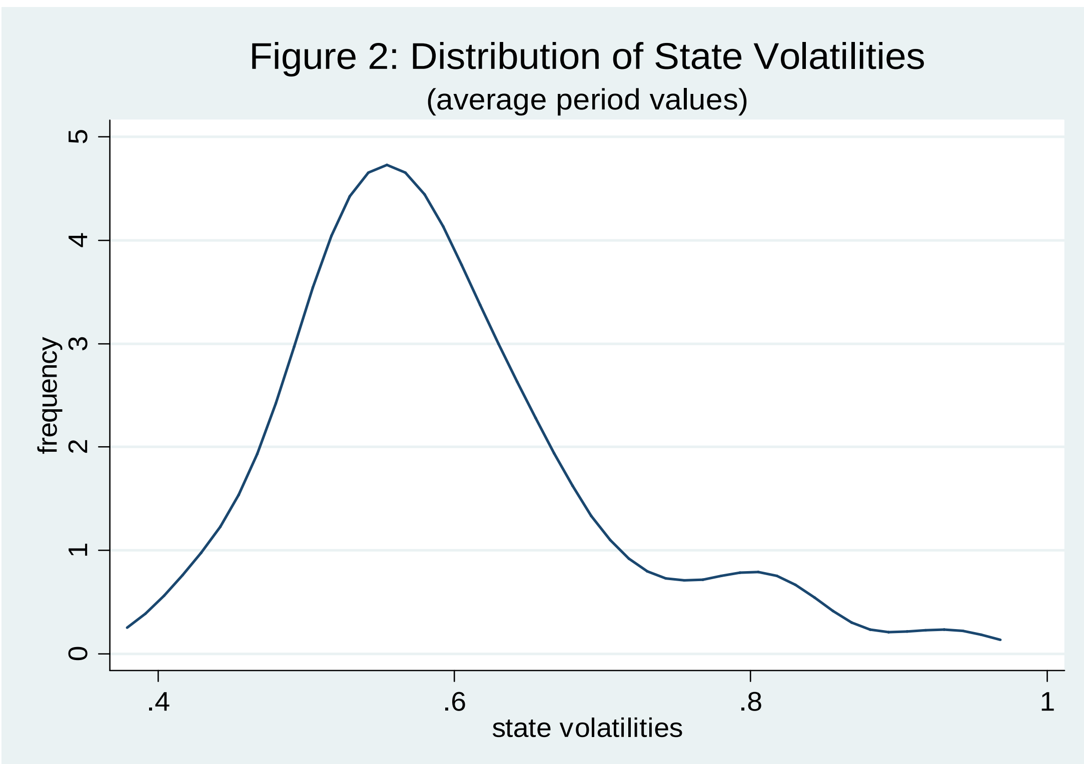
Figure 2: Distribution of State Volatilities
(average period values)
frequency
5
4
3
2
1
0
.4
.6
.8
1
state volatilities

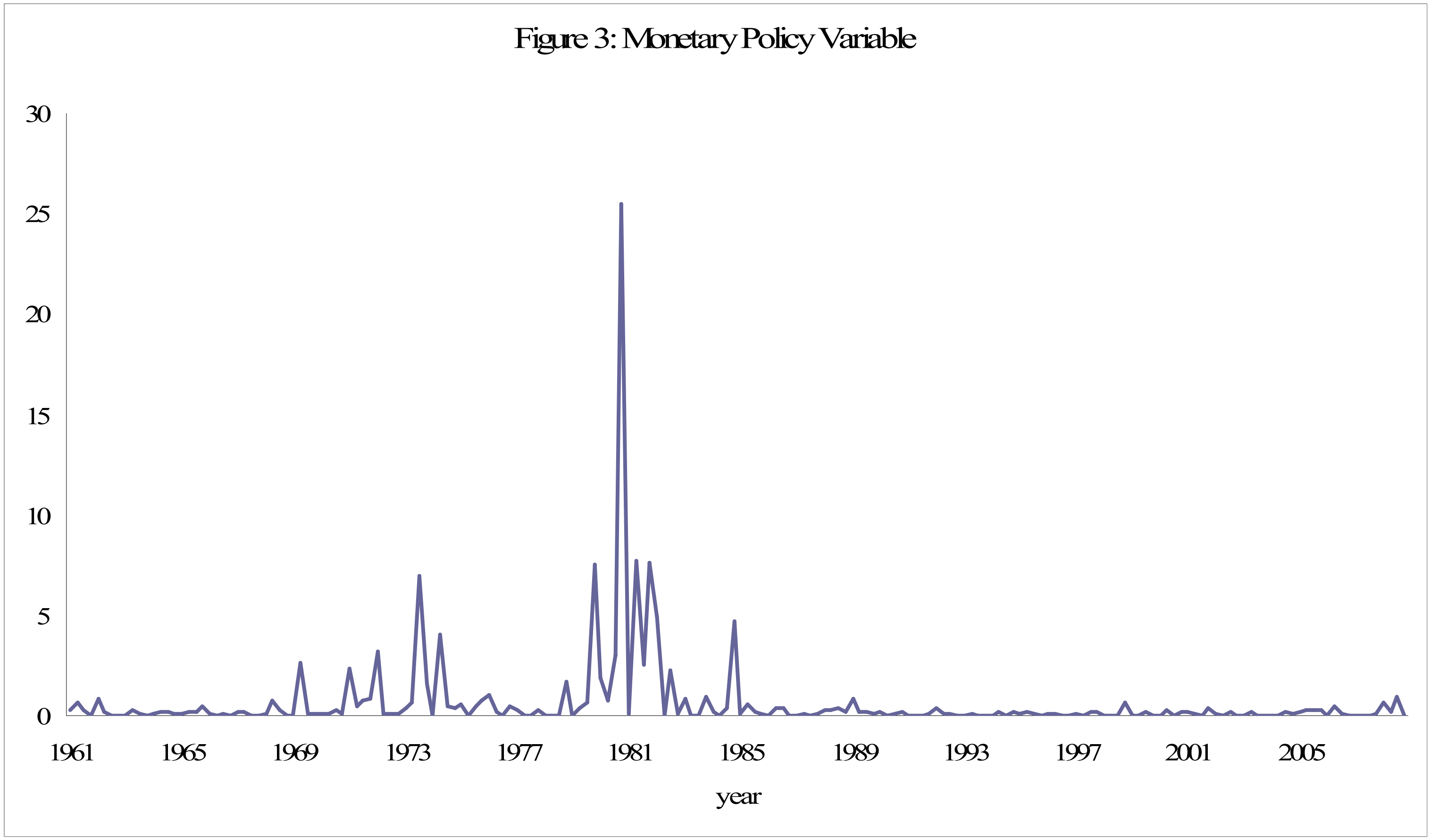
Figure 3: Monetary Policy Variable
30
25
20
15
10
5
0
1961
1965
1969
1973
1977
1981
1985
1989
1993
1997
2001
2005
year

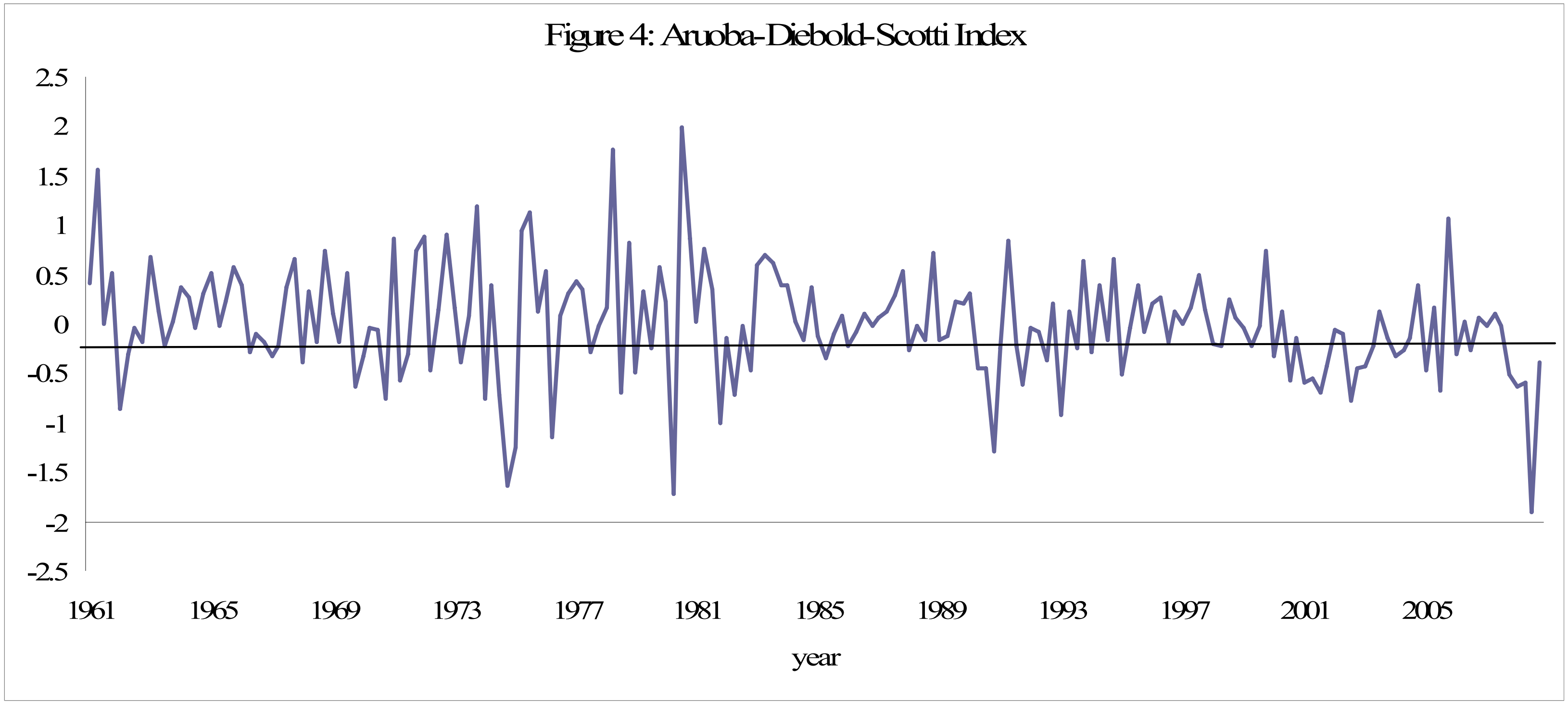
Figure 4: Aruoba-Diebold-Scotti Index
2.5
2
1.5
1
0.5
0
-0.5
-1
-1.5
-2
-2.5
1961
1965
1969
1973
1977
1981
1985
1989
1993
1997
2001
2005
year

Figure 5: Hamilton Net Oil Price Increase