



**DEPARTMENT OF ECONOMETRICS
AND BUSINESS STATISTICS**

**The Decline in Income Growth Volatility in the United States:
Evidence from Regional Data**

Heather Anderson and Farshid Vahid

The Decline in Income Growth Volatility in the United States: Evidence from Regional Data*

Heather Anderson and Farshid Vahid[†]

Department of Econometrics and Business Statistics

Monash University

Clayton, Vic 3800

Australia

November 2003

Abstract

We use US regional and state data to determine which regions have contributed most to the apparent decline in income growth volatility in the United States. We study changes in the variance of income growth in each region, changes in the covariance of growth between regions and changes in regional income growth shares. We establish that there has been a significant decline in the income growth volatility in thirty eight US states, and it is this, rather than changes in income shares, that is mostly responsible for the decline in the aggregate growth volatility. Further, we find that the twelve states that show no significant decline in their income growth volatility, are states with policies that make them unattractive to new businesses. We suggest that state level industrial policy may be a good, albeit partial, explanation for the decline in income growth volatility of the United States.

Keywords: Business location decisions, Composition effects, Diversification, Output growth volatility, Regional and state level income.

JEL classification: C22, E30, L22.

*This work was supported by the Monash University Outside Studies Program. We wish to thank the Economics Department at the University of California, San Diego, for providing an excellent environment for visiting scholars, and we give special thanks to Gordon Hanson for introducing us to the literature on business location decisions. The usual disclaimer applies.

[†]Correspondence: E-mail: Heather.Anderson@BusEco.monash.edu.au.

1 Introduction

A simple plot of quarterly growth rates of the US GDP against time (shown in Figure 1) shows that the variability of output growth has decreased since the mid-eighties. Since Kim and Nelson (1999) and McConnell and Perez-Quiros (2000, hereafter MCPQ) showed that this decrease was statistically significant with a break-point at 1984:1, there has been a growing literature on this issue. This literature is mainly concerned with the question of whether the decline in the variability of the output growth has been due to (a) good luck (smaller shocks to the economy), (b) good policy, or (c) a structural change. The significance of this distinction is that each explanation has a different implication about the permanency of decrease in volatility. The first answer implies that output growth volatility can go back to the pre-eighties level at any time. The second answer implies that we can sustain the low variance as long as there are no major changes in policy. Finally, the third answer implies that the changes are here to stay, regardless of possible policy changes.

MCPQ (2000) look at the sectorial components of GDP and find a significant break in the variance of consumer durables. They look further into the durable goods sector, and find no statistically significant evidence of a break in the final sales of durable goods, which implies that the entire change in the variance of durable goods production must have been due to a decrease in the volatility of the inventory process. Since the policy sensitive durable goods sales do not show any significant change in variance, they interpret their findings as evidence for the hypothesis that structural change in the production and inventory control of the durable goods sector is responsible for change in the volatility of output growth in the United States. In Kahn et. al. (2001), the durable goods sector is examined further, and the contribution of information technology to inventory management is chosen as the important determinant of decline in the variance of durable goods production.

Ramey and Vine (2002) examine the automobile industry as a major representative of the durable goods sector in the United States. They show that a small decline in the variance of the sales process can lead to a large decline in the variance of the production process because there are nonconvexities in the cost function of this industry. This shows that the observed decline in the variance of durable goods production can be explained by the small decline in the variance of (policy sensitive) durable goods sales, without any need for a structural change in the production process.

The decline in the variability of output growth is not specific to the USA. Blanchard and Simon (2000) find that similar, but not coincident, declines are observed in all G-7 countries except Japan. They also show that in each of the six countries where output growth volatility has declined, there has been a coincident

decline in the volatility of the inflation rate. Aziz and Vahid (2003) study the Australian case (see Figure 2), finding structural change in GDP at the same date as for the US, but no structural change in durable goods production. Durable goods production is not a significant component of the Australian economy in any case. Van Dijk et al (2002) perform the break analysis on many monthly economic series for G7 countries. Their result for industrial production, which is the proxy for aggregate output in their data set, are similar to Blanchard and Simon's, with the exception that Van Dijk et al do not find a statistically significant break in the volatility of German industrial production growth. While other country volatility estimates seem similar to the US case in certain respects, the differences in the nature and timing of the decline in other countries lead both Blanchard and Simon (2000) and Van Dijk et al (2002) to conclude that the information technology revolution in inventory management cannot be a good explanation for the international evidence.

Blanchard and Simon (2000) and Van Dijk et al (2002) speculate that monetary policy might be behind the volatility declines observed in different countries. However, an alternative explanation might be that state level industrial policies may have contributed to this decline in volatility. In an interesting paper on the location choice of firms, Holmes (1998) finds that manufacturing location in the USA depends on the business climate within each state, with higher growth observed in those states that have pro-business laws. The relevance of this work here, is that attraction of new industries leads to *diversification* as well as economic growth, especially in those states that have traditionally relied on primary production, and this diversification reduces volatility in GDP growth. For example, it is quite conceivable that the choice of the Toyota corporation to establish its largest manufacturing plant outside of Japan in Kentucky, the growth of new PC industries in Texas (Compaq and Dell) and South Dakota (Gateway), and the establishment of new passenger and cargo airlines in Texas (Southwest), Tennessee (Fedex) and Georgia (UPS) have reduced the income growth volatility of these states. It might be this diversification, rather than, or as well as, monetary policy or changes in inventory management that has caused the volatility decline in the USA.

This paper looks at the volatility in regional and state level measures of US output. Our work is exploratory, and has the purpose of establishing whether the change in the variance of US output growth can also be seen in the variances of the growth in regional (and state) outputs. We aim to identify those regions that have been most influential in the apparent decline in the volatility of the aggregate. We find that the volatility decline is most evident in Southern and South-eastern states, whose governments have actively fostered a "pro-business climate" and have encouraged the entry of new industries. In contrast, those states that have not experienced volatility declines perform poorly in published rankings of state

business climates, and have not introduced right to work laws.¹ However, not all states that have experienced volatility declines are business friendly states. There are large states such as Pennsylvania, Ohio and Michigan which rank poorly in pro-business ranking but have experienced significant declines in growth volatility. These important exceptions prove that the location choice of manufacturing firms alone cannot be the sole reason behind the decline in growth volatility in the United States. However, our objective is to bring state policies to the attention of researchers who have so far only considered monetary policy in their discussion of whether “good policy” has caused the decline in growth volatility in the United States. We hope that this will introduce promising avenues for further research on the causes of volatility decline in other countries as well the USA.

The structure of our paper is as follows. In the next section, we explain the source and the quality of the regional and state measures of output. We present the results of our volatility analysis in Section 3, and relate our results to the industries that prevail in each region, and the state specific measures of business climate discussed in Holmes (1998). We conclude in Section 4

2 Data

All data used in this paper is from the Bureau of Economic Analysis (BEA)², and can be downloaded from www.bea.gov. We used regional quarterly personal income data, since regional quarterly GDP figures are not available. “State personal income” is the income received by the residents of the State from participation in production, from government and business transfer payments, and from interest payments. Personal income is basically GNP less (capital depreciation, corporate profits and net transfers from businesses to government) plus (personal interest and dividend income and transfers from government and business to persons). The magnitude of total personal income for the US has been larger than 80% of GNP during the postwar period, and it has approached 90% of GNP in recent years. The state and regional personal income data are consistent with aggregate data for the United States in the sense that they add up to the personal income figure recorded in the US national income and product accounts (NIPA). We consider individual states (50 states and the District of Columbia) and the eight regions of the United States, as defined by the BEA. These are:

1. New England Region (NENG): Includes Connecticut (CT), Maine (ME), Massachusetts (MA), New Hampshire (NH), Rhode Island (RI) and Vermont

¹Right to work laws give workers the right not to join a union.

²From here on, the paper does not consider any country other than the United States. Therefore, all agencies, regions, states and economic data refer to agencies, regions, states and economic data of the United States.

- (VT). The average share of this region in total US personal income over the 1954-2001 period is 6%.
2. Mid-East Region (MEST): Includes Delaware (DE), District of Columbia (DC), Maryland (MD), New Jersey (NJ), New York (NY) and Pennsylvania (PA). The average share of this region in total US personal income over the 1954-2001 period is 22%.
 3. Great Lakes Region (GLAK): Includes Illinois (IL), Indiana (IN), Michigan (MI), Ohio (OH) and Wisconsin (WI). The average share of this region in total US personal income over the 1954:2001 period is 19%.
 4. Plains Region (PLNS): Includes Iowa (IA), Kansas (KS), Minnesota (MN), Missouri (MO), Nebraska (NE), North Dakota (ND) and South Dakota (SD). The average share of this region in total US personal income over the 1954:2001 period is 7%.
 5. South East Region (SEST): Includes Alabama (AL), Arkansas (AR), Florida (FL), Georgia (GA), Kentucky (KY), Louisiana (LA), Mississippi (MS), North Carolina (NC), South Carolina (SC), Tennessee (TN), Virginia (VA) and West Virginia (WV). The average share of this region in total US personal income over the 1954:2001 period is 19%.
 6. South West Region (SWST): Includes Arizona (AZ), New Mexico (NM), Oklahoma (OK) and Texas (TX). The average share of this region in total US personal income over the 1954:2001 period is 8%.
 7. Rocky Mountain Region (RKMT): Includes Colorado (CO), Idaho (ID), Montana (MT), Utah (UT) and Wyoming (WY). The average share of this region in total US personal income over the 1954:2001 period is 3%.
 8. Far West Region (FWST): Includes Alaska (AK), California (CA), Hawaii (HI), Nevada (NV), Oregon (OR) and Washington (WA). The average share of this region in total US personal income over the 1954:2001 period is 16%.

All state and regional personal income figures are nominal and are seasonally adjusted. In the absence of state and regional price indices, we calculated real personal income figures by deflating the nominal data with the US GNP chain-type price index. Quarterly personal income data is available from 1948:1, but we only use the data from 1954:1, to maintain comparability with other studies of US output variance. Our sample contains 192 observations and finishes at 2001:4.

The biggest problem with using personal income as a proxy for GDP is that some individuals can put forward or delay their wage payments to benefit from new tax policies³, and this generates ripples in quarterly growth rates around the

³We thank Kurt Kunze of the BEA for providing us with this explanation.

time of the policy change. This is recorded in NIPA tables under the title of “WALD: wage accruals less disbursements”. Fortunately, this has happened only around the 1993 tax law changes in the period under study. In anticipation of tax law changes, some businesses put forward their next quarter’s wage payments to the fourth quarter of 1992, which shows up as \$63 billion more disbursements than accruals for 1992:4, and then as \$72 billion less accruals than disbursements for 1993:1. Later, in 1993:4 and 1994:1, WALD figures were -\$50.2 billion and +\$56 billion. In all other quarters, the WALD component is almost zero. These large WALD components produce large ripples in the personal income growth rates for 1992:4, 1993:1, 1993:2, 1993:4, 1994:1 and 1994:2. Although, the WALD figures can be added back to the personal income figures at the national level to correct for such timing manipulations, state and regional WALD figures are not available to correct the state and regional figures. Therefore, we ignore the period from 1992:4 to 1994:2 in our regional analysis. Figure 3 plots the growth rates of real quarterly personal income and real GDP for the US. As illustrated, the largest discrepancy between the two is during the 1992:4 to 1994:2 period, which is shaded on the graph.

Figure 4 shows the quarterly growth rates of real personal income for each of the 8 regions⁴. The observations from 1992:4 to 1994:2 are not shown, and pre and post 1984:1 observations are separated by solid lines⁵. Although not as pronounced as the aggregate GDP figures, it can be seen that the volatility of personal income growth has decreased since the mid-eighties in some regions. In the remainder of this paper, we study these breaks and their effects on the aggregate.

3 Empirical Analysis

3.1 Composition effects

The growth rate of an aggregate is not the simple average of growth rates of its components. If we denote the personal income of region i at time t by y_{it} , its growth rate by g_{it} , the aggregate income by Y_t and its growth rate by G_t , then we have

$$G_t = \frac{\Delta Y_t}{Y_{t-1}} = \frac{\sum_i \Delta y_{it}}{Y_{t-1}} = \sum_i \frac{y_{it-1}}{Y_{t-1}} \times \frac{\Delta y_{it}}{y_{it-1}} = \sum_i w_{it-1} g_{it}$$

where w_{it-1} is defined as the share of region i in total income at time $t - 1$, and $\sum_i w_{it-1} = 1$. The decomposition shows that the growth rate of aggregate income is a weighted average of regional growth rates⁶. Therefore, at least part of the reduction in the variance of the aggregate may be due to compositional effects,

⁴We do not provide plots for state incomes to save space.

⁵We use 1984:1 to divide our data because it corresponds to the break in US aggregate volatility found by MCPQ.

⁶Obviously this result applies to the state level growth rates as well.

i.e. a decrease in the share of high variance regions and an increase in the share of low variance regions. Figure 5 shows the evolution of income shares of the eight regions. Even though there have been some clear compositional shifts away from the “north” and “mid-west” and towards the “south” and “west”, the income shares change very smoothly, and too smoothly to be able to create abrupt shifts in aggregate variance. To see this more clearly, we constructed a constant share aggregate growth series G_{0t} using:

$$G_{0t} = \sum_i w_{i0} g_{it}$$

where w_{i0} is the income share of region i at the beginning of the sample period. We then compared the rolling window estimates of the standard deviations of G_t and G_{0t} using a window of ten years (40 observations), starting from the beginning of the sample period and sliding the window one observation at a time. The two series of variance estimates are so close that they are indistinguishable in a time series plot. Obviously we obtain similar results when we fix the vector of shares to be $w_{i\tau}$, where $w_{i\tau}$ denote the shares at any point τ in time. Similar results are obtained when we consider the state level data. We therefore conclude that the composition changes cannot be responsible for the observed decline in the variance of aggregate income growth.

Taking shares as constant and denoting them by the vector \mathbf{w}_0 , the variance of the aggregate growth rate is

$$V(G_t) = \mathbf{w}_0' V(\mathbf{g}_t) \mathbf{w}_0$$

where \mathbf{g}_t is the vector of regional growth rates. We further note that

$$V(\mathbf{g}_t) = \text{diag}(\sigma_{it}) \times \Lambda(\mathbf{g}_t) \times \text{diag}(\sigma_{it})$$

where σ_{it} is the standard deviation of the growth rate for region i and $\Lambda(\mathbf{g}_t)$ is the correlation matrix of regional growth rates. One might next ask how much of the time variation in the aggregate is due to variation in the pairwise regional correlations. To answer this question, we fix the correlations to values estimated from the pre-1984 observations. Then, we construct a series of estimates of the variance of aggregate income growth, using fixed weights and fixed correlations, but time-varying rolling window estimates of the regional standard deviations. This estimated series and the rolling window estimate of the actual variance of aggregate income growth are plotted in Figure 6. The graph shows that the fixed correlation variance underpredicts the true variance in the periods of high volatility, and over predicts the true variance when this variance is low. This provides some evidence that correlations increase whenever variances increase, and they decrease whenever variances decrease⁷. Nevertheless, the pattern of

⁷This is sometimes called the “contagion effect” in finance. See, for example, Forbes and Rigobon (2002).

time variation in the overall variance can be seen in the fixed correlation variance as well, which shows that time variation in the regional variances is the more important factor in producing changes in the aggregate variance. The results of a similar exercise using state level data are qualitatively the same.

3.2 Dating of the regional breaks

Table 1 shows the shares of each region in aggregate income in the first six years of the sample (1954-1959) and the six years before 2001, i.e. (1995-2000)⁸, together with some analysis of income growth volatility. The share data shows that the four southern and western regions have experienced higher than average income growth, while all other regions have experienced lower than average income growth. The volatility analysis is based on estimates of the most likely break dates for those regions where the null hypothesis of ‘no break in volatility’ is rejected at the 5% level of significance. The break tests that we conducted are based on an auxiliary regression of the absolute value of errors from an AR(p) on a constant and a shift dummy variable, with the lag length of the AR model being selected by the Hannan and Quinn criterion. The test statistic is the maximum of all LM test statistics for a change in variance over all break dates that are not too close to either end of the sample. Since variance regressions are likely to be heteroskedastic (see Davidian and Carroll (1987)), we base the test on the maximum of heteroskedasticity consistent LM tests. The distribution of this statistic is derived in Andrews (1993), and p-values can be calculated using Bruce Hansen’s programs which are based on Hansen (1997).

The break date of the volatility in US aggregate personal income growth is estimated to be 1984:4. This is not exactly the same as the date of the break estimated using GDP data (i.e. 1984:1), but it is close to and not statistically significantly different from it. The most likely break dates for the Great Lakes and South East regions are 1984:1 and 1984:4. For the other regions which show statistically significant breaks in their growth variance, the Plains region’s break is estimated to be 1984:2, and the South West and Rocky Mountain regions both have 1987:1 as their break dates. Table 1 also shows that, in instances where there has been a significant change, the decline in regional volatility has been greater than the 30% reduction observed in aggregate volatility, and if not for the large Mid-Atlantic and Far West regions, the decline in US income volatility might well have been more than forty percent. Concentrating on the four economically larger regions (Mid-East, Great Lakes, South East and Far West), and using 1984:1 as the hypothesized break point, we find statistically significant evidence of a break in the variance of personal income growth for only the Great Lakes and South East regions.

⁸We did not include 2001-2002 to exclude the effects of September 11, 2001.

We concentrate on the two large regions, Great Lakes and South East, which show significant breaks in their growth variance. The rolling window estimates of the variances of these two regions are plotted in Figure 7 (a) and (b), which clearly support a break in variance close to the time of the break in the aggregate. In fact, both series look quite similar to the aggregate series. This is not true for other regions, and we have plotted the analogous series for the Far West region in Figure 7 (c) for contrast⁹. This shows that the break in the variance of US personal income growth is a reflection of the break in the variance of the Great Lakes and South East regions. As the change in their income shares reveal, although the Great Lakes and South East regions have experienced similar declines in the variance of income growth, they have had diametrically opposed growth experiences. Great Lakes has been the slowest growing region and the South East has been the fastest growing region in the United States in the period under study. This has important implications for the marginal effect of a possible increase in volatility of the income of either of these states on the US income volatility.

The variance of aggregate income depends on income shares, regional correlations and regional variances. Our analysis shows that shares have changed smoothly over time. It also shows that regional correlations change, not as smoothly as shares, but not too abruptly either. Both shares and correlations need to satisfy theoretical bounds, which limit how much shares and correlations can influence aggregate variance. However, the question of how much a small increase in the standard deviation of a specific region will increase the standard deviation of the aggregate, everything else equal, depends crucially on the regional weights and correlations. Using a rolling window of 40 observations, we have calculated these marginal effects for all regions and presented them in Figure 8. The overall trend in these contributions is similar to the trend in regional shares. The Mideast and Great Lakes regions have declined in importance, while the South East and Far West regions have gained. The most important information in this plot relates to recent data points. These show that a small change in the variance of the South East region will have the more influence on the variance of the aggregate, than small changes in variance elsewhere.

The Great Lakes and South East regions include major production centers of the automobile industry in the United States, and the observed decline in these regions provides some support for the hypothesis initially proposed by MCPQ (2000), that advances in inventory management in the durable goods sector are responsible for the reduction in output volatility. However, it is puzzling why such advances in technology have not led to similar effects in other regions such as the Far-West. Similarly, the “good luck” and “good policy” explanations ought to be about shocks and policies that affect the Great Lakes and South East, and do not

⁹When comparing these graphs, note the differences in the scale of the vertical axis.

affect the Mid-East and Far-West regions. We turn to more disaggregated state level data for a possible explanation.

3.3 Why has volatility not declined everywhere? Evidence from state level data

The states in BEA regions are not necessarily homogenous. Table 2 provides information about breaks in the volatility of personal income in the fifty states and the District of Columbia. The states are sorted in descending order of their share in total US income in 1995-2000. All but twelve states show evidence of a decline in volatility sometime during the sample period, and from all states that do show evidence of a break, only two very small states (Vermont and Wyoming) reject the hypothesis that the break could be in 1984:1. However, it is interesting that from the ten largest economies in the US, which together account for more than 56 percent of the US national income, five, headed by California and New York, show no sign of a volatility decline.

In addition to the information about shares and volatility, the last two columns of this table provide information about business climate in the states used in Holmes (1998). The state’s “pro-business” rank, in a ranking based on 15 characteristics of state policy designed by Fantus Consulting in 1975, is recorded under the heading of “Fantus rank”. The state ranked 1 (Texas) is the state with the friendliest conditions for business, and the state ranked 48 (California) provides the most anti-business climate. Alaska, Hawaii and the District of Columbia are not ranked. The last column of Table 2 shows whether the state has “Right to Work” laws or not. A right to work law gives workers the right not to join the union. Holmes (1998) provides evidence that clearly shows that manufacturing firms locate in states with a pro-business climate. Given that states with a pro-business climate are mostly southern and agricultural states, it is only natural that the attraction of manufacturing industry to these states will lower income variance as the base of the economy becomes more diversified.

It is interesting to note that all twelve states that did not experience a decline in volatility, did not have right-to-work laws. We construct a dependent variable ($\%change_i$), which is zero for the twelve states that have not experienced a significant decline in volatility, and is equal to the actual percentage change in volatility for all other states. A Tobit model of this dependent variable with the “Fantus rank” ($BusRank_i$) and pre-break magnitude of the variance of the state ($InitVar_i$) as explanatory variables is reported in equation (1)¹⁰.

$$\begin{aligned} \%change_i &= \frac{-39.18}{(-3.94)} + \frac{0.75}{(2.94)} BusRank_i - \frac{11.29}{(-2.99)} InitVar_i + \hat{e}_i & (1) \\ R^2 &= 0.34 \end{aligned}$$

¹⁰The reported t-statistics (in brackets) have been corrected for heteroskedasticity.

This equation shows that the less pro-business a state is (i.e., the larger its *BusRank_i* is), the more likely it is that the state has not experienced a decline in variance (remembering that the dependent variable is either zero or negative). It also shows that given *BusRank_i*, the states with larger initial variance are likely to have experienced a larger percentage decline in their growth volatility. Since initial growth variances are highly correlated with the relative importance of agriculture in the economy of each state at the beginning of the sample, this finding is consistent with the view that diversification of the economy of these states is an important reason for the decline in output growth volatility in the United States. We obtain qualitatively similar results from a linear regression model, which has the percentage change in the growth variance of each state before and after 1984:4, regardless of the statistical significance of the change, as the dependent variable. The same is true for a probit model, which has a binary dependent variable that shows if a state has experienced a significant decline in growth volatility. Replacing the “Fantus rank” with the “right-to-work law” indicator, where applicable, produces the same conclusion: states with pro-business policies and larger initial variances are more likely to have experienced a decline in volatility.

We do not intend to stretch this conclusion too far, in the sense that we do not claim that the decline in volatility in every state has been due to increase in diversity of that state’s economic base as a result of the attraction of new industries. After all, this does not explain the decline in the variance of income growth in Pennsylvania, Ohio, Michigan and the Great Lakes region. Our intention is to argue that state’s industrial policies should also be looked at as well as Federal macroeconomic policies, in explaining the recent decline in output volatility in the United States and also internationally.

4 Conclusion

There is little doubt that uncertain times are here again, and this will lead to higher variation in output and other economic variables. We can already feel increased volatility around us as the current political crisis unfolds. Some “shocks” can be identified with major historical events such as the World Wars, which have a beginning and an end. Others are less clear cut, such as the “oil shocks” in the seventies. Perhaps the reason why the break in the volatility of the output in the mid-eighties has attracted so much attention is that no major historical event happened at that time (although some may disagree, given the tumbling of oil prices over the eighties). Certainly, we have been lucky that the “shocks” in the eighties and nineties have been transient. But at the same time, the United States have witnessed a southward shift of capital and labour, the information technology revolution and unprecedented innovation in capital markets. Is the US economy now better prepared to absorb unprecedented “shocks” and avoid going

back to a period of high income variance?

We suggest that an important step towards understanding how shocks affect the volatility of aggregate US output is to understand how they affect different regions of the US, and in particular the South East region of the US. We find that the combination of this region's increasing share in total income, its pairwise correlations with other regions and the present level of regional variances, has made the South East region the most influential region for the volatility of aggregate income. This region has successfully attracted many new industries because of its pro-business policies. Attraction of new industries has diversified the economies of this region, and this diversification has decreased the variance of the income growth rate in this region. This diversification must have made this region's personal income, and its contribution to the aggregate income, more robust to shocks.

References

- [1] Andrews, D.W.K. (1993). "Tests for Parameter Instability and Structural Change with Unknown Change Points", *Econometrica*, 61, 821 - 856.
- [2] Aziz, A. and F. Vahid (2003). "What has Caused the Decline in Australian Output Volatility?", mimeo, Department of Econometrics and Business Statistics, Monash University, Australia.
- [3] Blanchard, O. and J. Simon (2001). "The Long and Large Decline in U.S. Output Volatility", *Brookings Papers on Economic Activity*, 2001:1, 135 - 174.
- [4] Davidian, M. and R.J. Carroll, (1997). "Variance Function Estimation", *Journal of the American Statistical Association*, 82, 1079 - 1091.
- [5] Forbes, K.J. and R. Rigobon (2002). "No Contagion, Only Interdependence: Measuring Stock Market Comovements", *The Journal of Finance*, 57, 2223 - 2261.
- [6] Hansen, B.E. (1997). "Approximate Asymptotic P-values for Structural Change Tests", *Journal of Business and Economic Statistics*, 15, 60 - 67.
- [7] Holmes, T.J. (1998), "The Effect of State Policies on the Location of Manufacturing: Evidence from State Borders", *Journal of Political Economy*, 106, 667-705.
- [8] Kahn, J.A., M.M. McConnell and G. Perez-Quiros (2002) "On the Causes of Increased Stability of the U.S. Economy", Federal Reserve Board of New York *Economic Policy Review*, 183-202.

- [9] Kim, C.J. and C.R. Nelson, (1999). "Has the US Economy become more Stable? A Bayesian Approach Based on a Markov Switching Model of the Business Cycle", *The Review of Economics and Statistics*, 81(4), 1 - 10.
- [10] McConnell, M.M. and G. Perez-Quiros (2000). "Output Fluctuations in the United States: What has changed since the Early 1980's", *The American Economic Review*, 90 (5), 1464 - 1476.
- [11] Ramey, V.A. and D.J. Vine, (2003). "Tracking the Source of the Decline in GDP Volatility", mimeo available from the Department of Economics at the University of California San Diego website.
- [12] van Dijk, D., M. Sensier and D.R. Osborn (2002). "Changes in Variability of the Business Cycle in the G7 Countries", mimeo available from the Centre for Growth and Business Cycle Research website at <http://www.ses.man.ac.uk/cgbcr/discussi.htm>.

Figure 1: Growth rate of US GDP

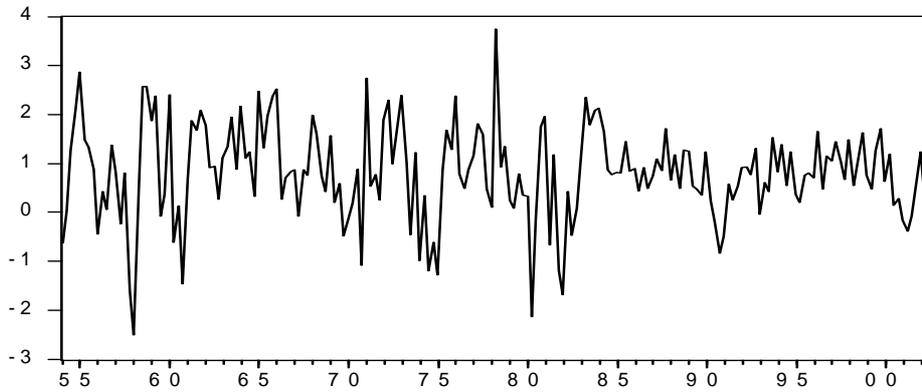


Figure 2: Growth rate of Australian GDP

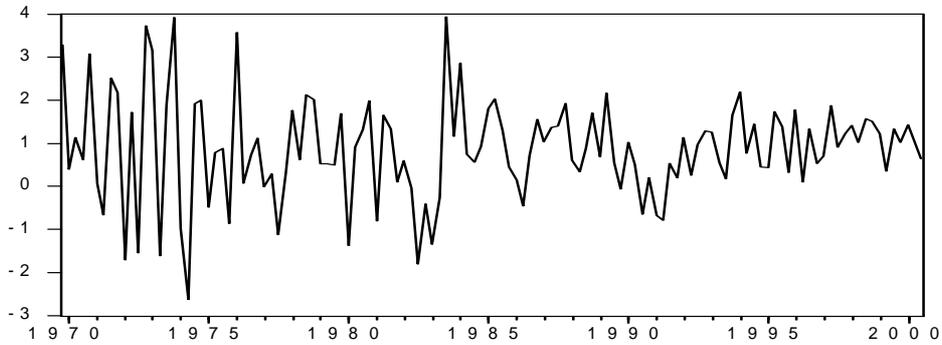


Figure 3: Growth rates of US GDP and US personal income
(Shaded area is when some wage disbursements were forwarded in response to tax policy change)

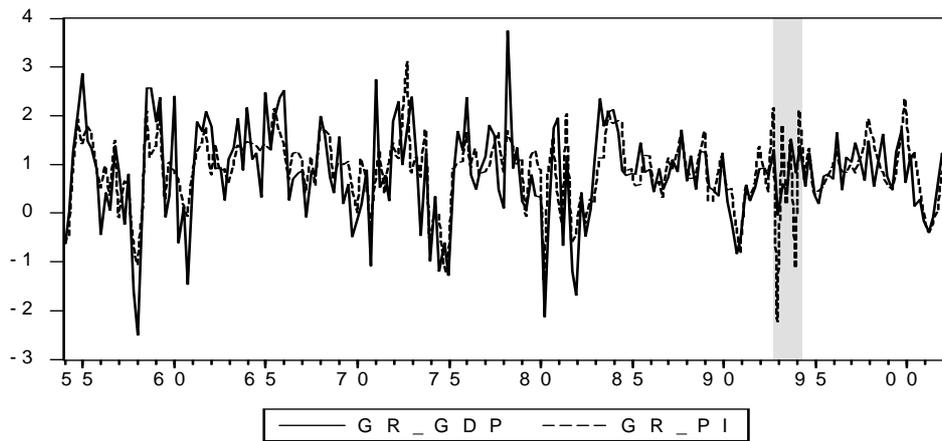


Figure 4: Growth rates of regional personal incomes

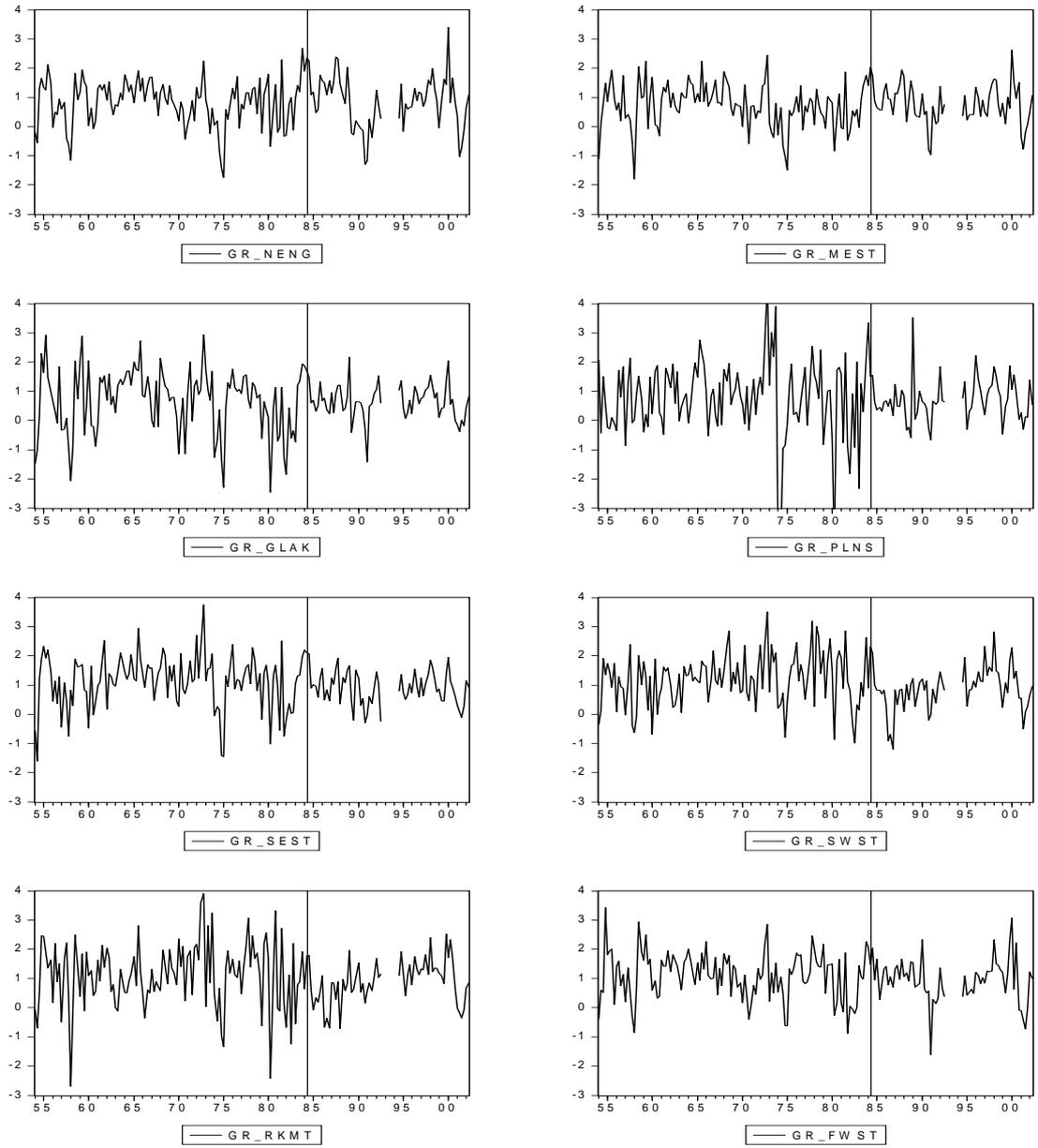


Figure 5: Evolution of regional income shares

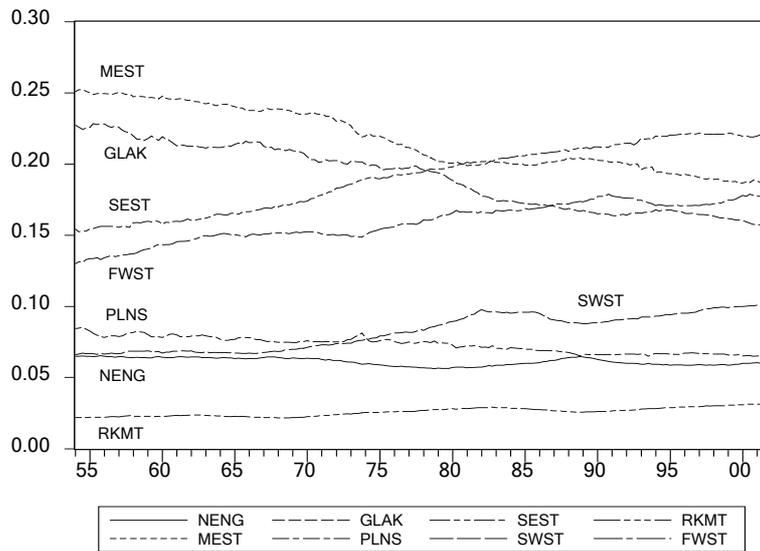


Figure 6: Rolling window estimates of the actual variance (solid line) and the fixed correlation variance (broken line) of the US personal income. The horizontal axis shows the end of the ten year window.

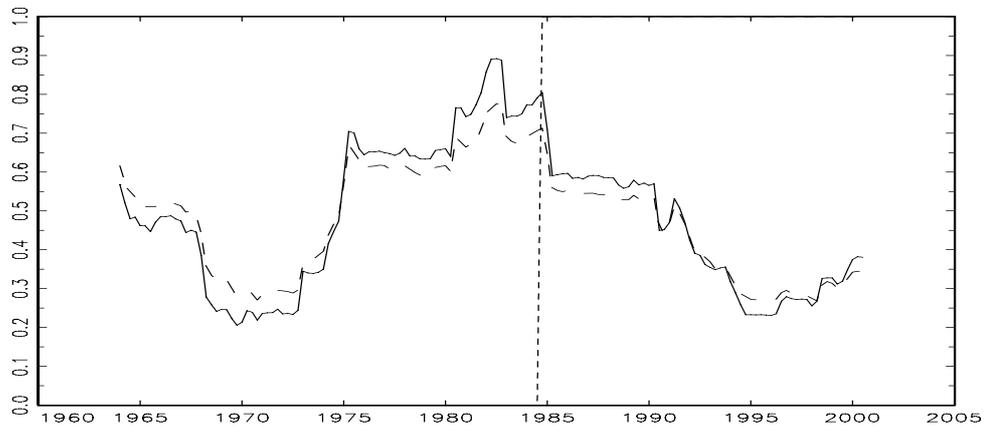
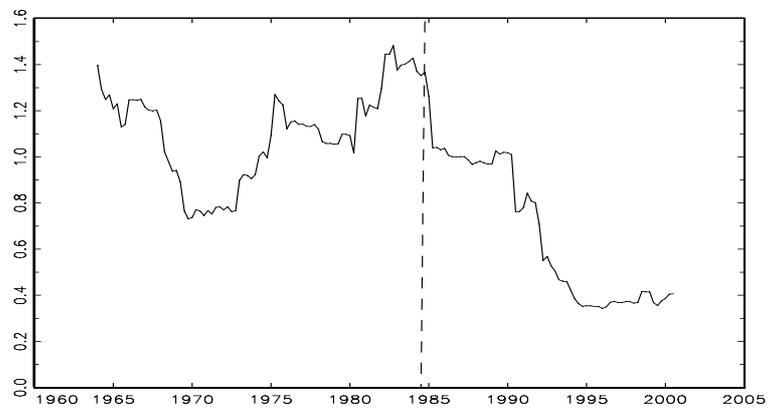
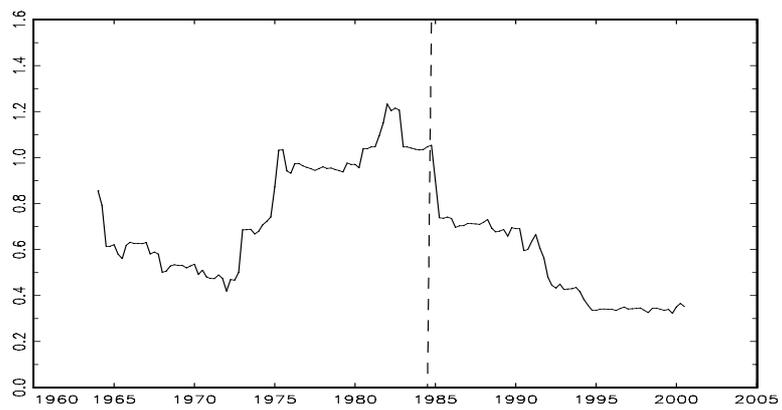


Figure 7: Rolling window estimates of the variance of personal income growth in selected regions of the US

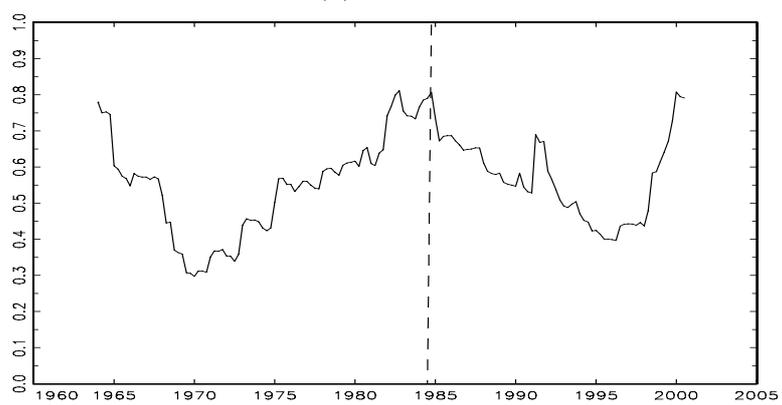
(a) Great Lakes



(b) South East

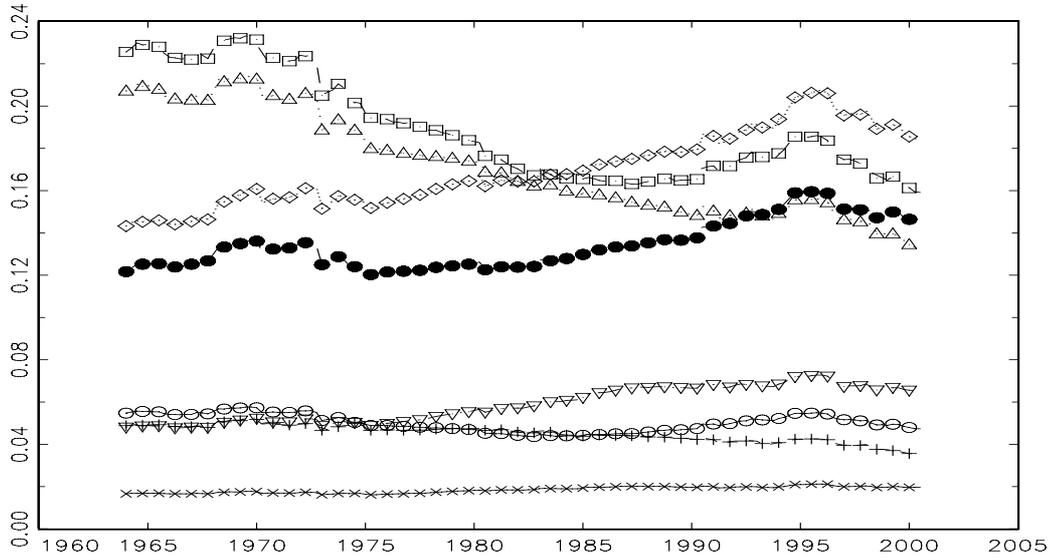


(c) Far West



Note the differences in the scale of the vertical axis when comparing these graphs.

Figure 8: Marginal effects of a change in regional standard deviations



NENG: empty circles MEST: rectangles GLAK: upright triangles PLNS: plus signs
 SEST: diamonds SWST: upside down triangles RKMT: crosses FWST: solid circles

Table 1: Regions, their income share and their income volatility.

Region	Share 54-59	Share 95-2000	Most likely break date	Pre- variance	Post- variance	Perc. change
Total US	100.00	100.00	1984:4	0.779	0.541	-30.50
New England	6.46	5.91	no break	N/A	0.821	N/A
Mid-East	24.90	18.99	no break	N/A	0.730	N/A
Great Lakes	22.32	16.34	1984:1	1.108	0.612	-44.81
Plains	8.08	6.63	1984:2	1.345	0.712	-47.08
South East	15.65	22.07	1984:4	0.917	0.535	-41.66
South West	6.74	9.77	1987:1	0.927	0.621	-33.05
Rocky Mountains	2.25	3.00	1987:1	1.118	0.656	-41.36
Far West	13.60	17.30	no break	N/A	0.787	N/A

Table 2: States, their income share and their income volatility

State	Share 54-59	Share 95-2000	Most likely break date	Pre- variance	Post- variance	Perc. change	Fantus rank	Right-to- Work law
California	10.20	12.62	no break	N/A	0.842	N/A	47	no
New York	11.55	8.01	no break	N/A	0.849	N/A	48	no
Texas	4.67	6.76	1987:2	0.969	0.710	-26.69	1	yes
Florida	2.18	5.43	1992:3	1.146	0.515	-55.06	7	yes
Illinois	6.80	4.87	no break	N/A	0.849	N/A	35	no
Pennsylvania	6.60	4.49	1983:4	0.992	0.541	-45.43	42	no
Ohio	5.85	3.99	1984:1	1.149	0.604	-47.46	27	no
New Jersey	4.05	3.76	no break	N/A	0.837	N/A	37	no
Michigan	4.90	3.61	1982:2	1.786	0.922	-48.36	45	no
Massachusetts	3.18	2.78	no break	N/A	0.879	N/A	46	no
Georgia	1.62	2.68	1984:4	1.105	0.682	-38.26	13	yes
Virginia	1.88	2.62	1984:4	1.039	0.693	-33.28	3	yes
North Carolina	1.80	2.58	1984:4	1.311	0.815	-37.86	6	yes
Washington	1.73	2.17	no break	N/A	1.071	N/A	39	no
Maryland	1.80	2.15	1985:2	0.935	0.616	-34.14	36	no
Indiana	2.58	2.01	1984:2	1.488	0.774	-48.00	9	no
Missouri	2.34	1.88	1984:2	1.010	0.502	-50.25	19	no
Minnesota	1.79	1.87	1991:2	1.212	0.741	-38.84	41	no
Wisconsin	2.19	1.86	1984:2	1.014	0.553	-45.46	34	no
Tennessee	1.43	1.82	1984:3	1.076	0.632	-41.24	15	yes
Connecticut	1.82	1.68	no break	N/A	0.955	N/A	43	no
Colorado	0.95	1.59	no break	N/A	1.060	N/A	18	no
Arizona	0.58	1.5	1982:4	1.324	0.851	-35.70	16	yes
Louisiana	1.36	1.31	1987:1	1.152	0.524	-54.53	26	yes
Alabama	1.23	1.31	1988:3	1.183	0.430	-63.65	2	yes
Kentucky	1.24	1.19	1985:2	1.275	0.702	-44.95	22	no
South Carolina	0.84	1.17	1991:4	1.479	0.565	-61.77	5	yes
Oregon	1.01	1.15	1984:1	1.332	0.566	-57.49	40	no
Oklahoma	1.08	1.01	1987:2	1.597	0.613	-61.63	21	no
Iowa	1.46	0.96	1989:2	2.137	0.890	-58.35	14	yes
Kansas	1.18	0.91	1984:2	1.662	0.781	-52.98	20	yes
Mississippi	0.66	0.74	1986:4	1.812	0.588	-67.57	12	yes
Arkansas	0.62	0.73	1984:3	1.886	0.578	-69.37	8	yes
Nevada	0.19	0.68	1983:1	1.686	0.801	-52.51	32	yes
Utah	0.42	0.62	1988:2	1.068	0.630	-41.00	10	yes
Nebraska	0.74	0.59	1984:4	2.237	0.882	-60.56	17	yes
West Virginia	0.79	0.50	1989:4	1.912	0.469	-75.45	29	no
New Mexico	0.41	0.50	1987:1	1.004	0.574	-42.84	23	no
New Hampshire	0.32	0.47	no break	N/A	1.137	N/A	28	no
Hawaii	0.32	0.45	no break	N/A	1.386	N/A	-	
Maine	0.46	0.40	no break	N/A	1.079	N/A	30	no
Rhode Island	0.49	0.38	1991:2	1.093	0.690	-36.94	33	no
Idaho	0.32	0.37	1984:1	1.844	0.895	-51.47	25	yes
Delaware	0.58	0.29	1982:1	1.384	0.888	-35.85	44	no
DC	0.31	0.28	no break	N/A	1.411	N/A	-	
Montana	0.37	0.26	1989:2	2.866	0.781	-72.74	31	no
South Dakota	0.30	0.24	1984:2	4.107	1.281	-68.80	4	yes
Alaska	0.15	0.24	1987:2	2.690	0.893	-66.82	-	
Vermont	0.18	0.20	1995:1*	1.068	0.630	-41.00	38	no
North Dakota	0.28	0.20	1989:2	6.285	2.148	-65.82	11	yes
Wyoming	0.19	0.16	1989:3*	1.710	0.735	-57.04	24	yes