Tracking the State Economies at High Frequency: A Primer

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Abstract: Tracking the business cycle at the level of state economies and discerning the impact of fiscal and regulatory policies – as well as nationwide policies – on state economies has been hampered by a limited number of available set of high frequency indicators. In this paper, we review the data sources and series available for a cross-section of states, with discussion of the associated advantages and disadvantages. We provide estimates of the correlation and comovement of various indicators with state level real GDP, and how different indicators define turning points in state economies. Finally, we illustrate the usefulness of high frequency state level GDP by evaluating whether a particular state economy is performing in line with expectations.

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1. Introduction

In 2011, a number of states embarked upon radical changes in fiscal policy, with stress on tax and spending cuts. These measures were often accompanied by claims that such fiscal measures would serve to accelerate economic growth. Validation of such claims was hampered by the relative dearth of high frequency (i.e., monthly, quarterly rather than annual) data on macroeconomic indicators at the state level.

This state of affairs stands in stark contrast to that applying to the national economy. In measuring the *national* business cycle, researchers are provided with a plethora of data series that measure different aspects of the economy. GDP is released at a quarterly frequency, industrial production, employment and consumption, and income data at a monthly frequency. Various surveys (purchasing managers indexes) are also released at a monthly frequency, while some labor market data (unemployment insurance claims) are even released at the weekly frequency.

Until recently, one had to wait for a once-yearly release on annual GDP to gain insight on state-level production. Otherwise, one was forced to rely upon less comprehensive albeit higher frequency data – such as monthly employment data. Even then, the information is either not as detailed as it is at the national level, or is subject to higher degrees of measurement error.

In this paper, we examine the data available to the researcher interested, not in analyzing after the fact the determinants of state level economic activity over long stretches of time, but rather in evaluating the course of the economy, particularly in response to particular shocks, be they either external to the state, policy driven, or exogenous (e.g., weather, the international economy).

We first review the sources of high frequency data. We then assess the correlation and comovement of various macroeconomic indicators, and how different indicators indicate different dating for business cycles. Finally, we provide one example of the use of high frequency data to assess indirectly the impact of economic policies.

2. Sources of High Frequency Data

2.1 Labor Market Data

Each month, the Bureau of Labor Statistics releases statistics for each state's labor market. These data releases parallel the nation-wide releases, with estimates based upon the establishment survey (CES) and the household survey (CPS). These figures are usually released approximately two weeks after the release of the national estimates, and state level estimates are calculated in collaboration with the statistical agencies in each state charged with tabulating employment statistics.

We select four states with disparate characteristics – California, Wisconsin, Texas and Wyoming – to illustrate how the various series behave and comove. California is the largest state in the union, encompassing a diverse economy. Wisconsin is a Midwest state with a relatively high proportion of medium industry. Texas and Wyoming both possess resource based economies, but differ substantively in population size. Below, we show civilian employment and nonfarm payroll employment, both in thousands, and seasonally adjusted.

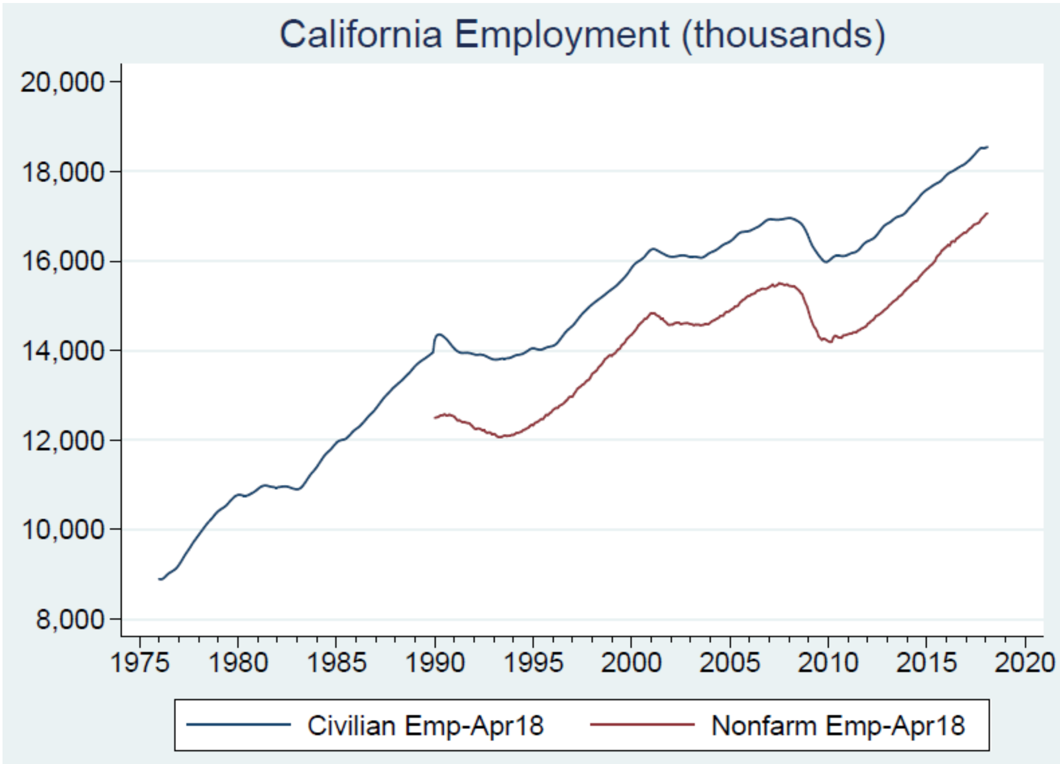

Fig 1.1: Nonfarm payroll employment and civilian employment for California

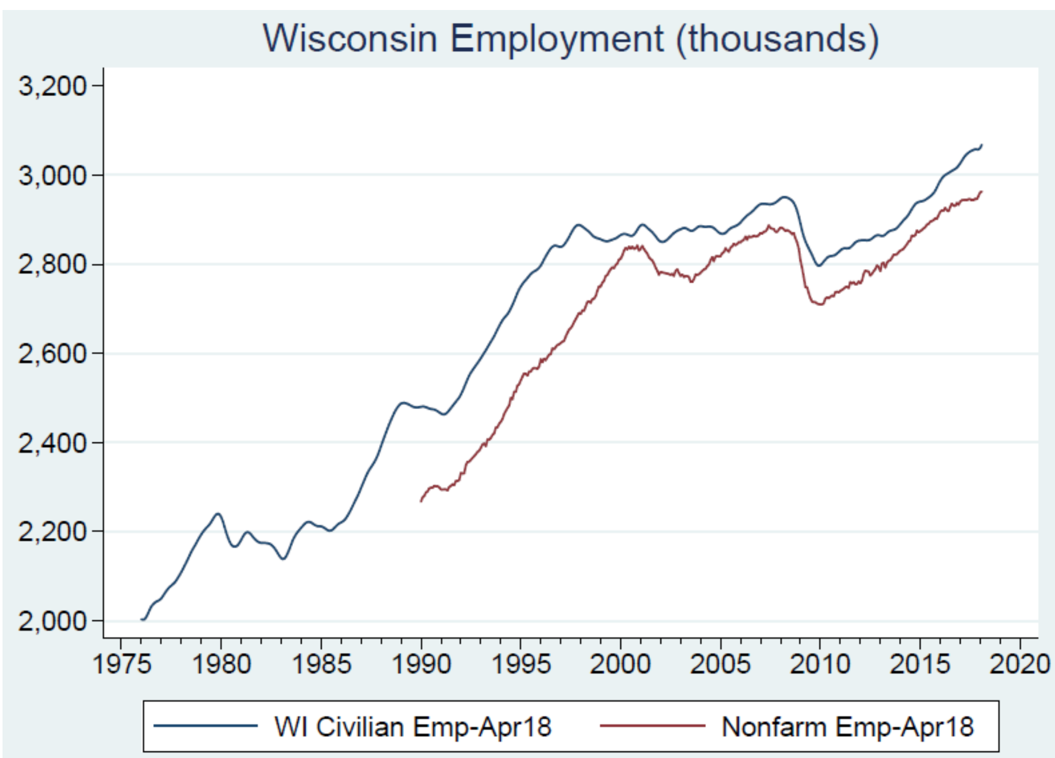

Fig 1.2: Nonfarm payroll employment and civilian employment for Wisconsin

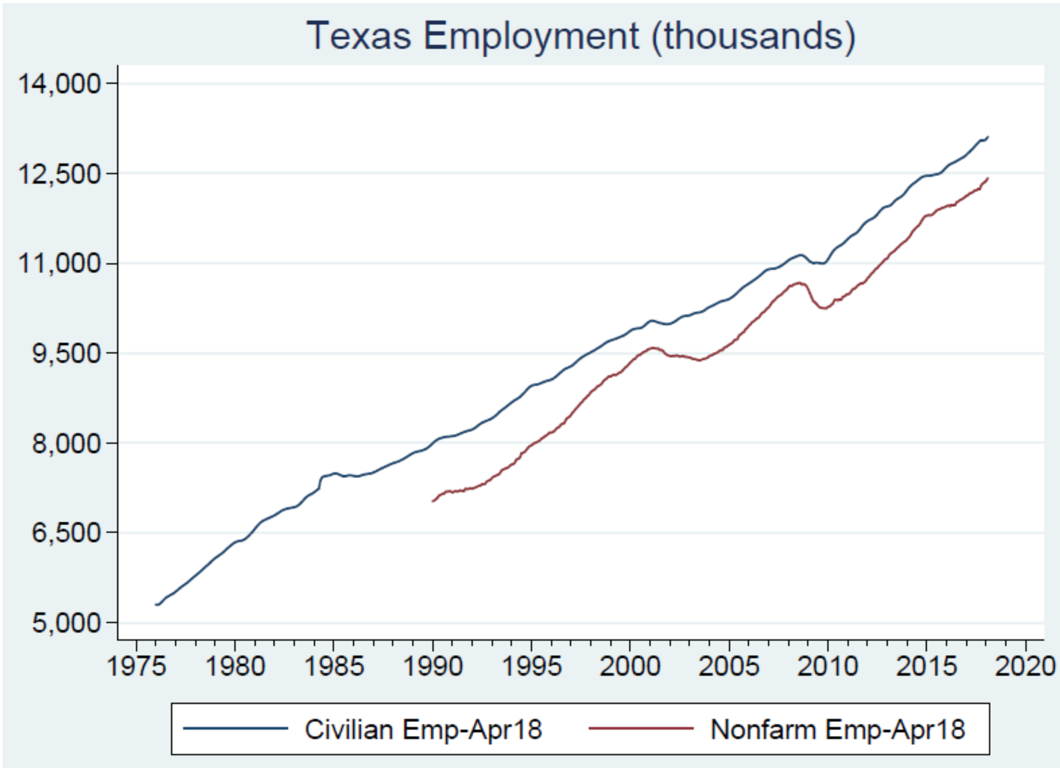

Figure 1.3: Nonfarm payroll employment and civilian employment for Texas

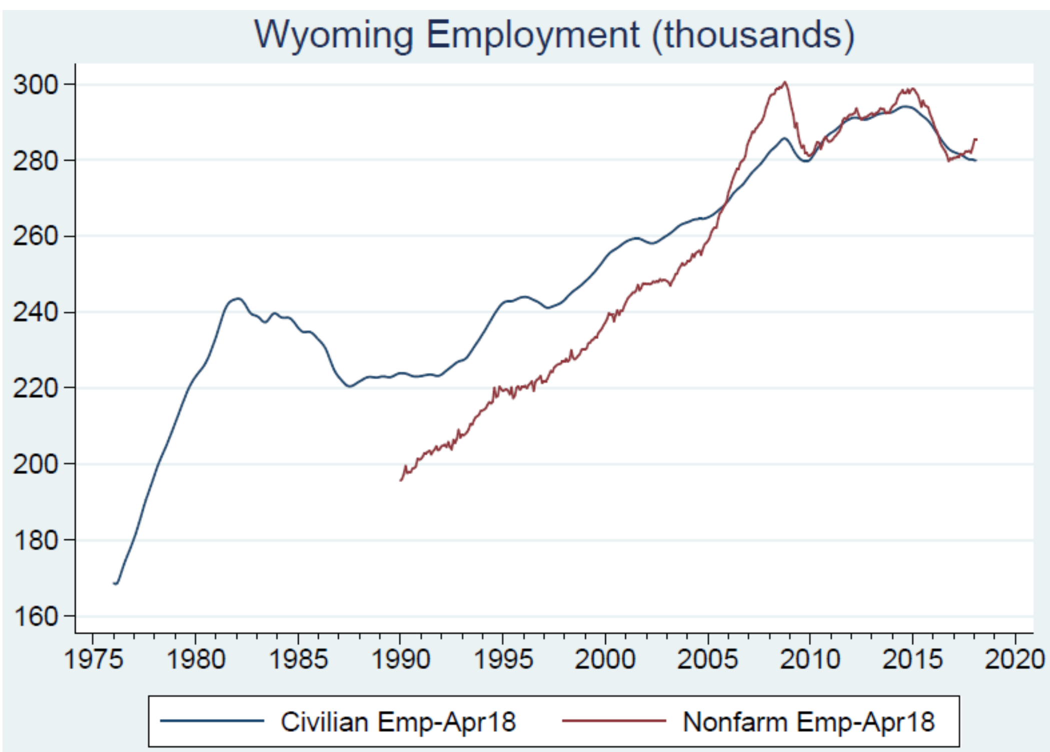

Figure 1.4: Nonfarm payroll employment and civilian employment for Wyoming

These two sets of surveys measure different aspects of the labor market, each with strengths and weaknesses.

2.1.1 The Establishment Survey and the Quarterly Census of Employment and Wages

The most widely reported series are the establishment series. BLS provides total nonfarm employment, private nonfarm payroll employment, and a breakdown to the industry level: agriculture, mining, manufacturing, services, and government, for instance. The state level establishment series are subject to greater (percentage) variability (from revisions) than the national counterpart, due in part to the smaller sample size.

Each year, the establishment series are benchmarked using Quarterly Census of Employment and Wages (QCEW) data. As the title indicates, the QCEW is a census, covering in principle all establishments. What the QCEW has in terms of accuracy, it loses in timeliness; there is usually a six month lag between the reference period and the release of the data.

In the following graphs, we display nonfarm payroll employment and the nearest corresponding series for the QCEW.

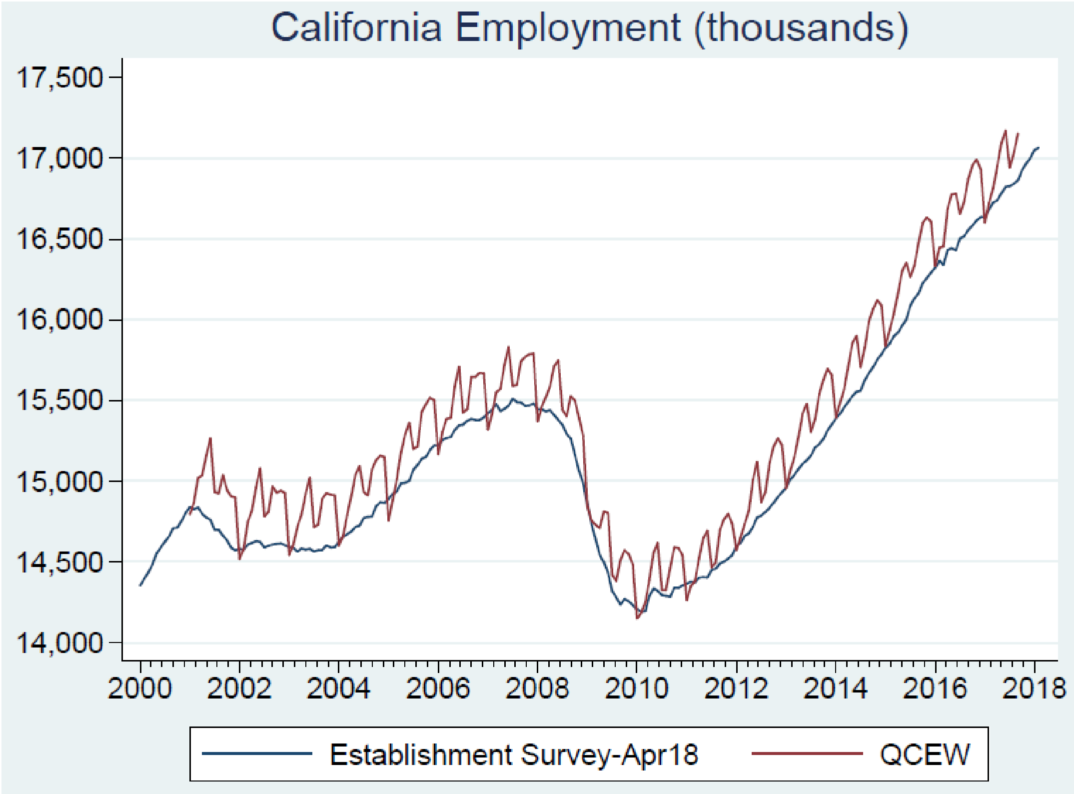

Figure 2.1: Nonfarm payroll employment and civilian employment for California

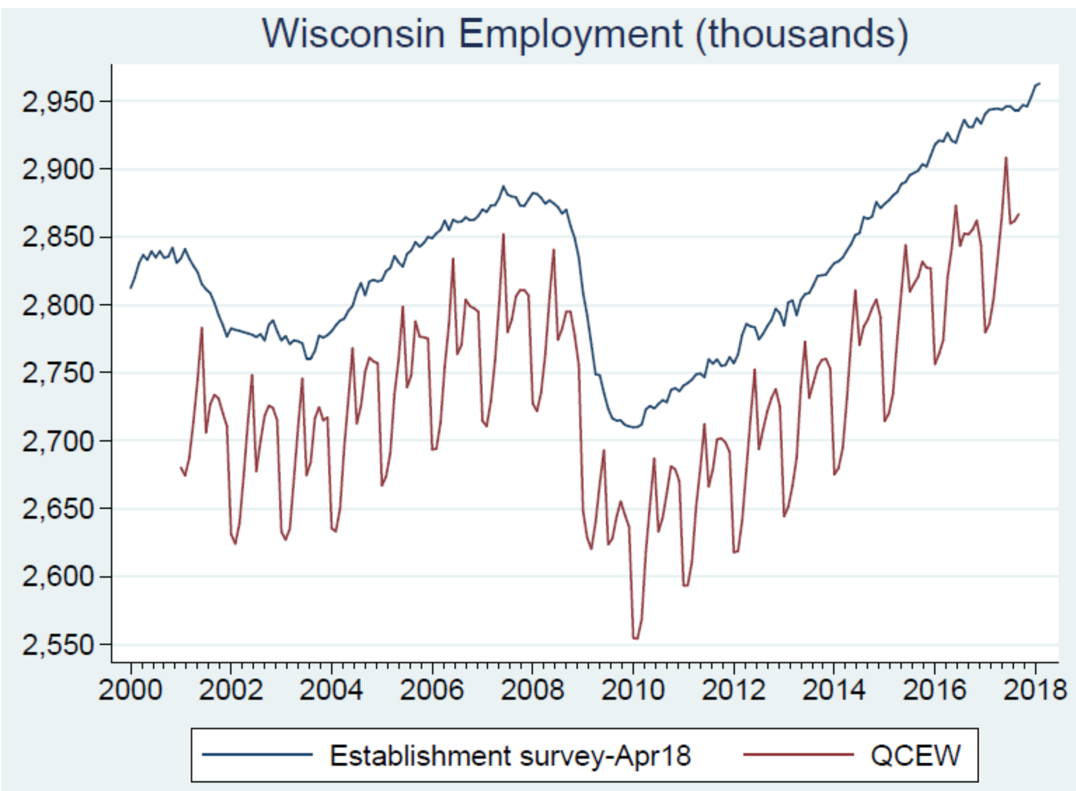

Figure 2.2: Nonfarm payroll employment and civilian employment for Wisconsin

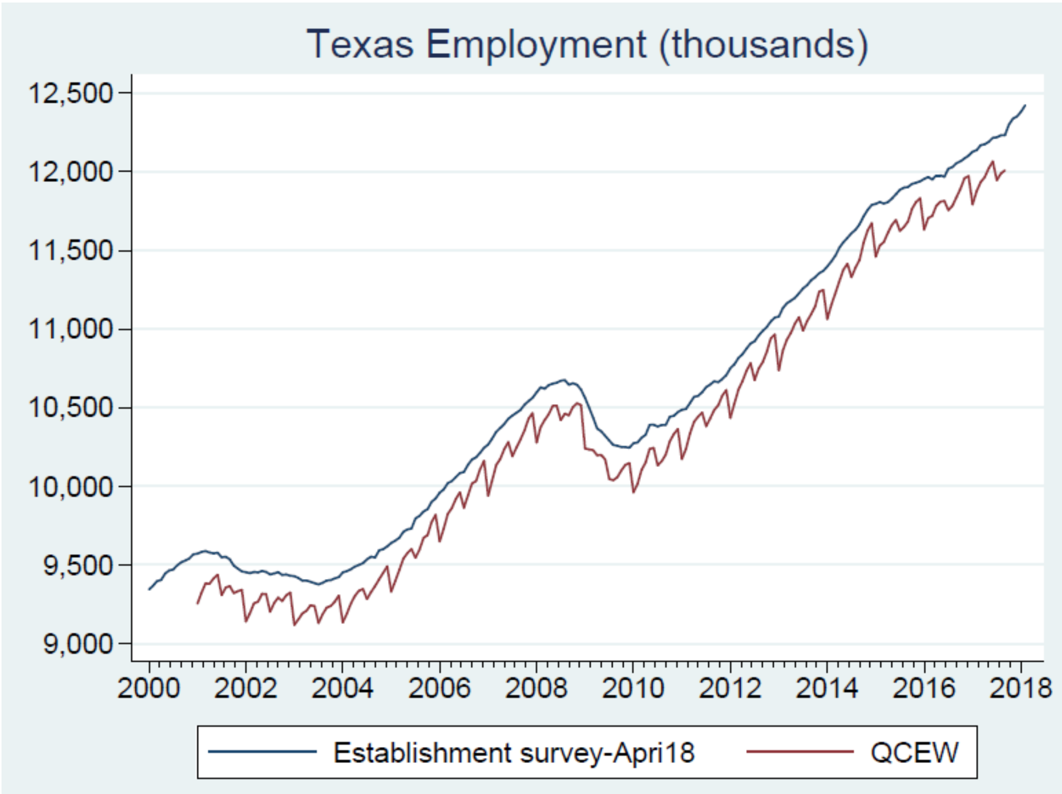

Figure 2.3: Nonfarm payroll employment and civilian employment for Texas

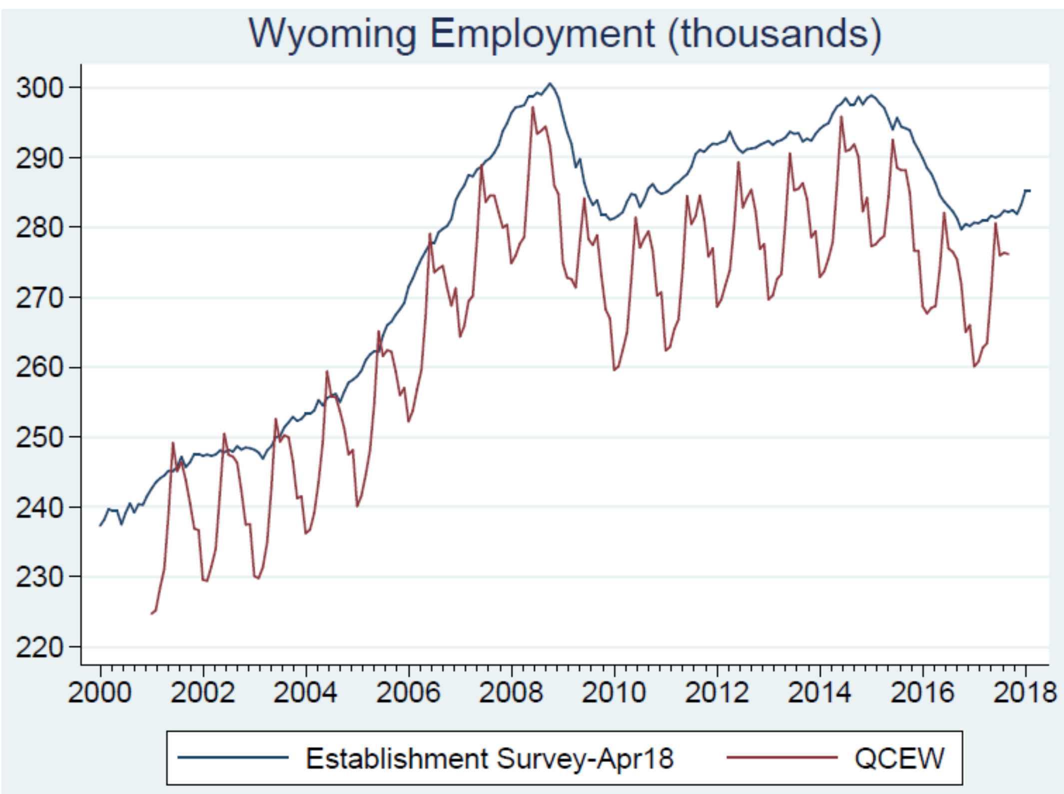

Figure 2.4: Nonfarm payroll employment and civilian employment for Wyoming

The incorporation of QCEW data occurs March of each year, based upon data reported up to September of the previous year. Ordinarily, one would not accord too much attention to such benchmarking procedures, except for the fact that with the revision in methodology, state level establishment series were subject to relatively large annual revisions, which sometimes changed the trajectory of measured employment growth markedly.

This last point is particularly important. This means that data reported after September of each year, before they are benchmarked, could be subject to potentially large revision. Hence, caveats applied to the focus on one month's nation-wide employment figures apply a fortiori to the state level data.[1]

2.1.2 The Household Survey

At the national level, the household survey applies to 60,000 households. In contrast, the establishment survey covers about 149,000 firms and government agencies. Obviously, with many, many more households than establishments, it will be more difficult to obtain a representative sample, even at a national level.[2]

When moving to the state level, these problems are compounded manifold. In fact, there are far too few households surveyed in a given state – except perhaps the very largest – to obtain usable estimates of employment, unemployment, and labor force participation. As a consequence, the BLS uses a time series model, including auxiliary variables like nonfarm payroll employment or unemployment

[1] See Mueller (2017).
[2] There are about 118 million households in the US, 2012-16 (Census Bureau, 2018); there are about 18,500 firms with more than 500 employees, and 27.9 million small firms (less than 500 employees), of which about 5.5 million had employees (SBA, 2012).

insurance figures, to estimate the relevant figures. In this sense, the household series at the national level and the state level are not constructed in the same manner.[3]

Perhaps more relevant, the degree of imprecision associated with the household survey based series at the state level makes them of more limited usefulness for inferring the direction of the economy. This is shown for the aggregate employment series (shown in figure 3) for California.

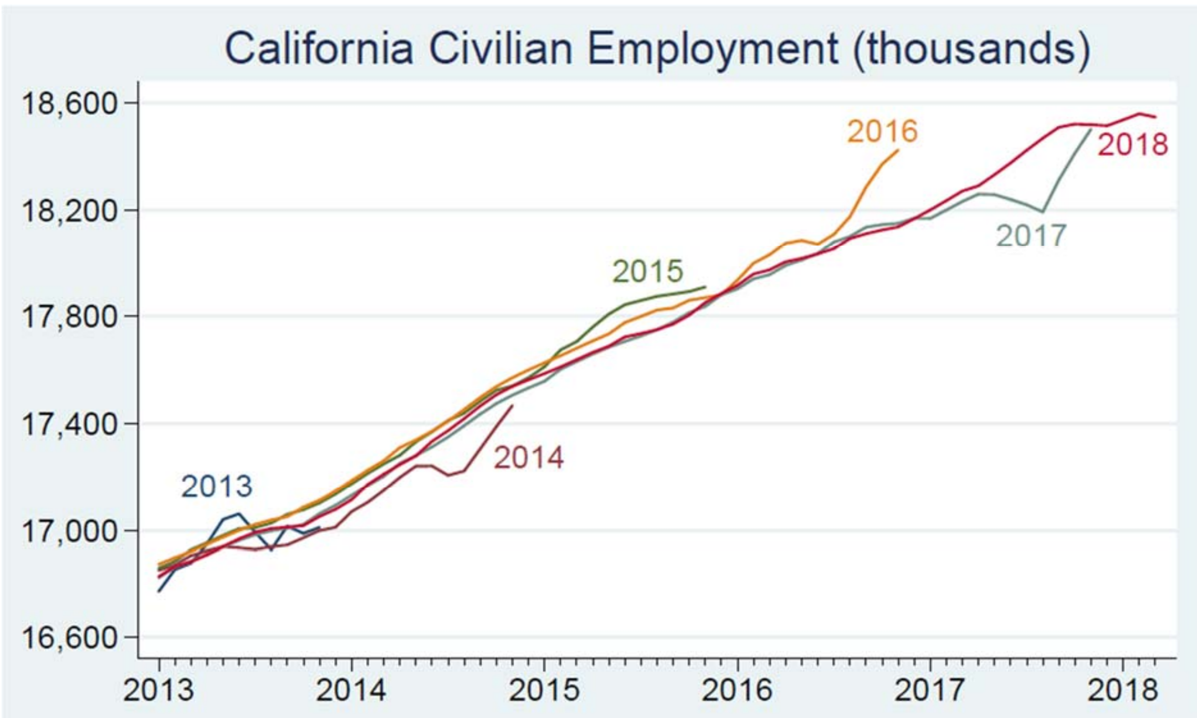

Figure 3. California, December releases of civilian employment for indicated years, except for 2018 (April).

One commonly used measure is the unemployment rate. This variable is the ratio of two variables, the employment series and the labor force series, both drawn from the household survey. The rate at the state level is less accurate than at the nation, as a consequence of sampling error and

[3] This is termed a "time-series signal-plus-noise model". The state level series are constrained to sum to the national series. See BLS (2014).

estimation method. For instance, the coefficient of variation for the state level unemployment rate when the unemployment rate is 6% is 8. In contrast, it is 1.9 at the national level (BLS, 2014: 2).

Observers sometimes make cross-state assessments by comparing unemployment rates. This is an ill-advised approach because some states have lower unemployment rates on average than the national rate, while others have higher. Wisconsin for instance has a lower rate than the national average (by about a percentage point) while California has a higher one (by about a percentage point).

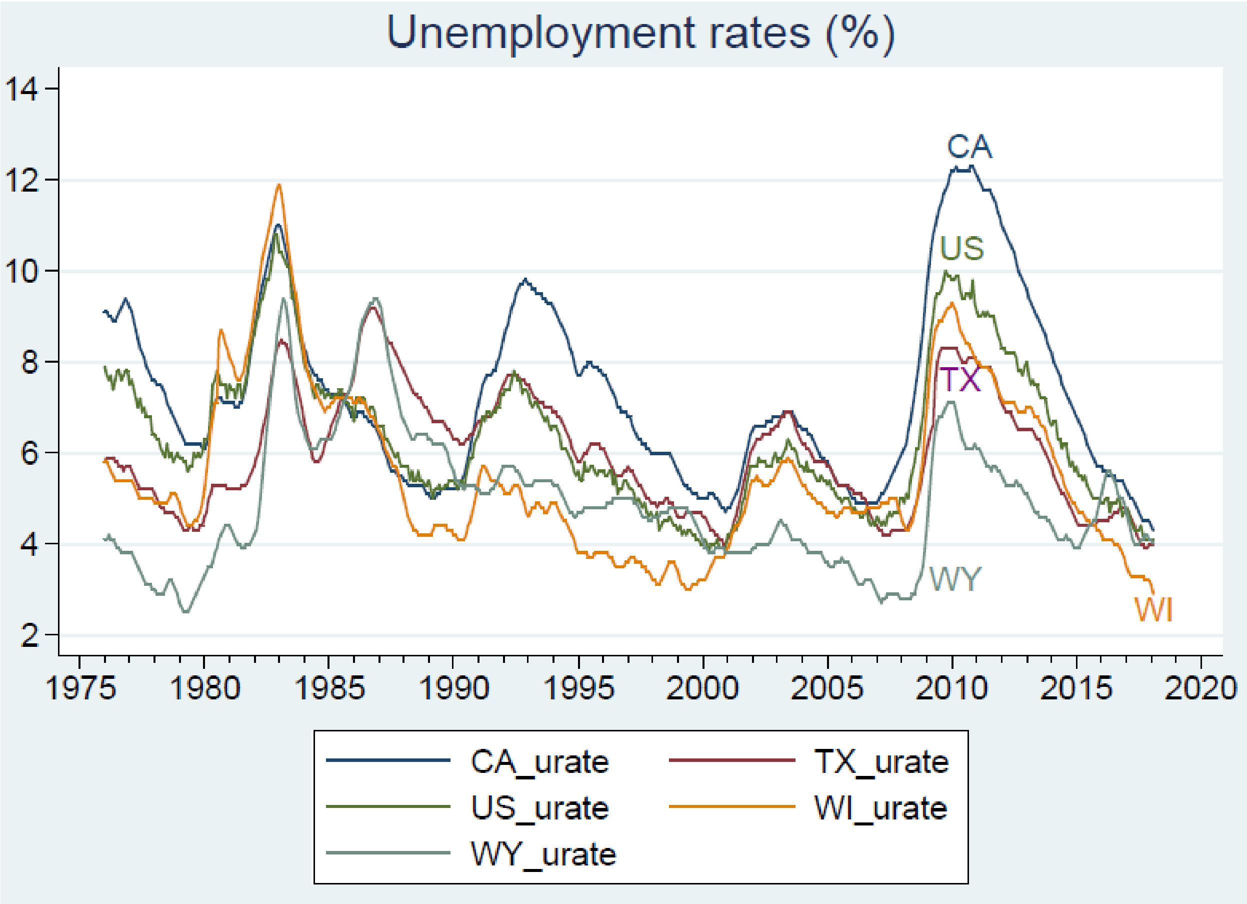

Figure 4. Unemployment rates

In this context, it makes little sense to stress, for instance, the unemployment rate in Wisconsin in May 2018 was the 5th lowest in the nation when it will on average have a lower rate than the national average, and hence be very highly ranked in terms of the unemployment rate.

2.2 GDP

As noted in the introduction, until recently, GDP at the state level was only released at an annual frequency. This changed in 2014, with the advent of a prototype quarterly GDP series. Now, GDP statistics were reported for the fifty states over the period 2005Q1 onward, in nominal and real terms[4]. Figure 5 depicts real GDP, normalized to 2011Q1=0, for four states and the nation.

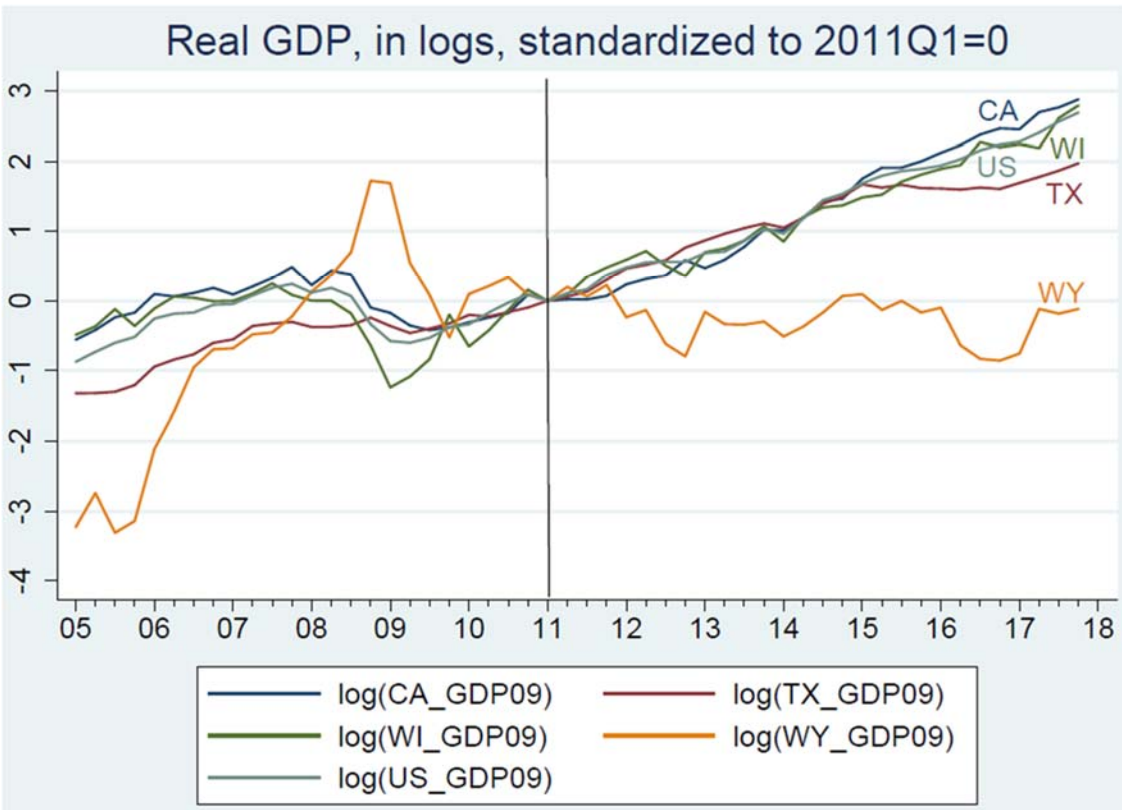

Fig 5. Real GDP, in logs, normalized to 2011Q1=0.

The state level GDP release also provides a sectoral breakdown of value added. This means that one can in principle discern in an accounting sense the contributions to economic growth arising from

[4] One important aspect of this data is that the price levels are not state specific. Rather, for each sector, the same deflator is applied across all states.

given sectors, e.g., agriculture versus manufacturing. This decomposition is shown for Wisconsin over the 2015-2017 period, in Figure 6.

The growth decomposition indicates that manufacturing value added growth accounted for a substantial, albeit volatile, share of aggregate growth in 2017. In contrast, agriculture value added has provided barely any support. It's important to recall in examining these figures that they are contributions in a mechanical, or accounting sense. It would not make much sense to say if, for instance, if the government contribution had been zero, rather than negative, in 2017Q2, output growth would've been 3% higher, on an annualized basis.

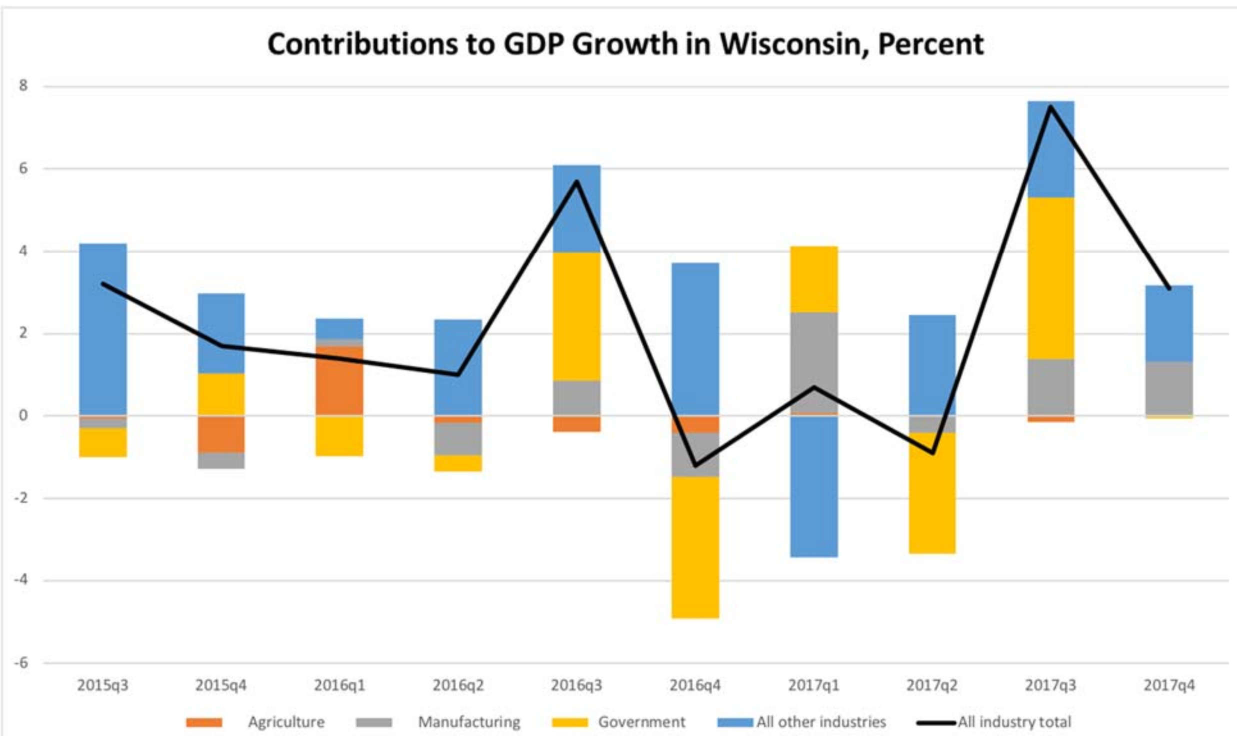

Figure 6: Contributions to Wisconsin real GDP growth, seasonally adjusted, at annual rates, in %.

It's important to note that these statistics differ from the most commonly reported GDP statistics available at the national level, namely the expenditure side components of GDP: consumption, investment, government spending, net exports. This expenditure breakdown is particularly useful for conducting Keynesian oriented analyses, with its focus on the multiplier process working through consumption, and investment fluctuations driven by movements in interest rates and credit formation.

While we do not have consumption data at the quarterly frequency, we do have personal income data at this frequency. These data are more timely than the GDP data. Figure 7 depicts personal income deflated by the *national* personal consumption expenditure deflator, and normalized to 2011Q1=0 (as in Figure 7).

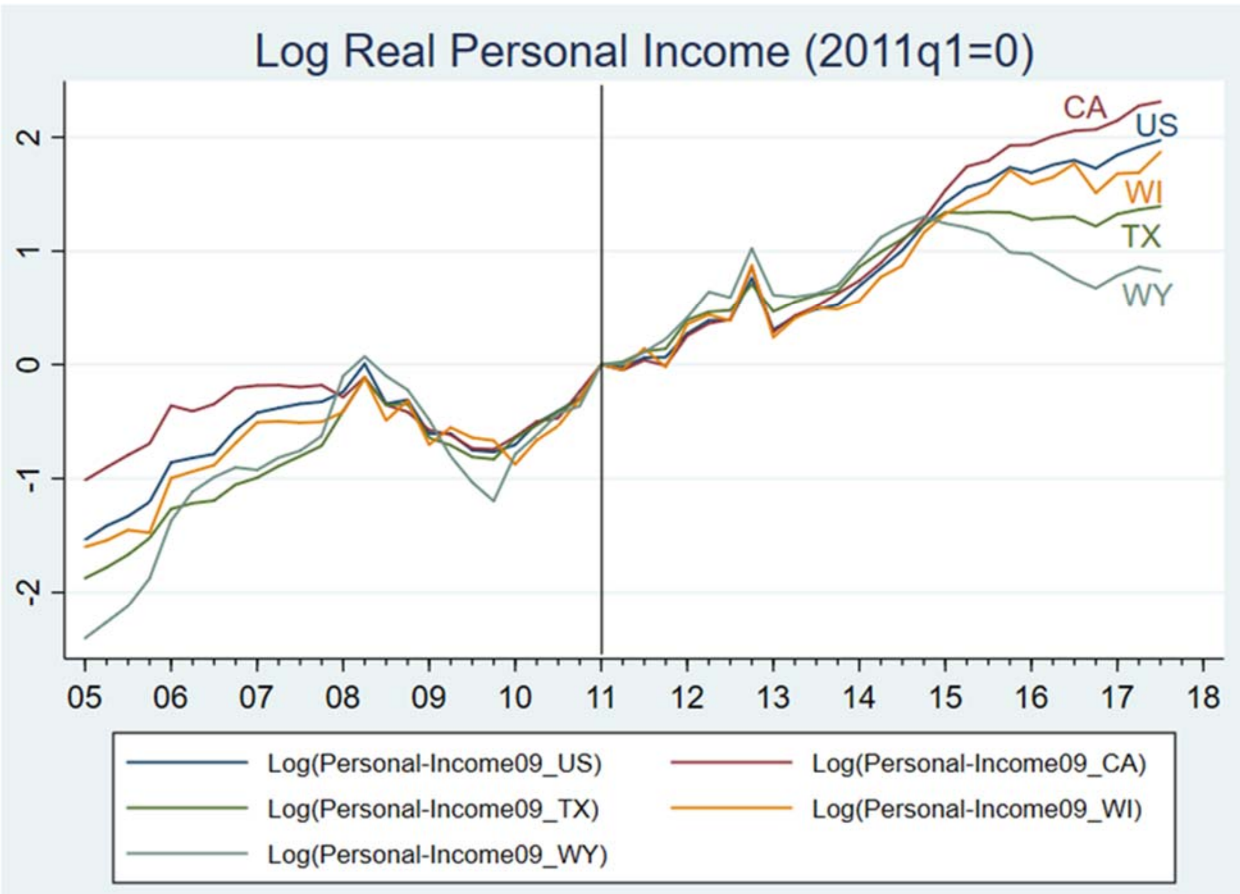

Figure 7: Real personal income, in logs, normalized to 2011Q1=0.

Notice that while the general trends are similar to those shown in Figure 5 – i.e., CA is above the US, while TX and WY below by the end of the sample – the shorter term movements do differ. This direct comparison is shown for Wisconsin in Figure 8.

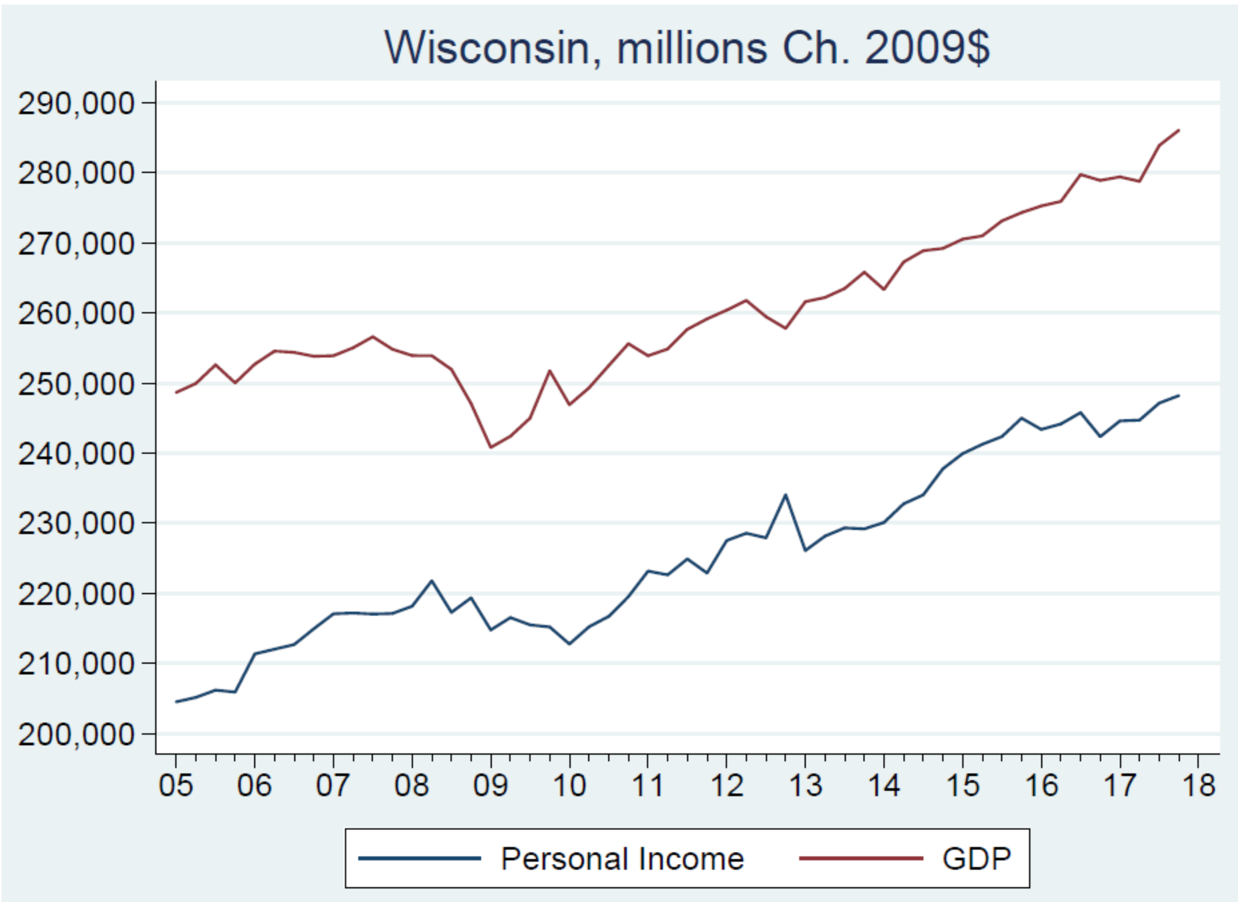

Figure 8: Real GDP and real personal income, in millions of Ch.2009$, SAAR.

2.3 Coincident Indices

Given the dearth of high frequency indicators for states economies, the Philadelphia Fed developed a measure that aims to summarize economic conditions, representing the economy more broadly than for instance labor measures (about the only series available at the monthly frequency). Recall, the BEA introduced quarterly GDP for the states only in 2016, and even at that juncture, extended back to only 2005.

The long period spanned by the coincident indices – they start from 1979 – has resulted in their widespread use in analyses of state-level business cycles. These include Owyang, et al. (2005), Beckworth (2010), Magrini et al. (2013), Brown (2017), and Aguiar-Conraria, et al. (2018).

The coincident indices combine four state-level indicators: nonfarm payroll employment, average hours worked in manufacturing by production workers, the unemployment rate, and wage and salary disbursements deflated by the CPI. The trend for each state's index is set to the trend of its gross domestic product (GDP); Crone and Clayton-Matthews (2005) describes the methodology used.

Following Stock and Watson's (1989) methodology for summarizing the state of the US economy, the Philadelphia Fed used a dynamic single-factor model create the state indexes. "The method involves a system of five major equations: one equation for each input variable and one equation for an underlying (latent) factor that is reflected in each of the indicator (input) variables. The underlying factor represents the state coincident index."

The advantage of the approach is that it is systematic and timely in its release. The drawback is that this methodology will have varying degrees of correlation with the target variable (GDP), depending upon how representative the four variables used as inputs are.[5] Novak (2013) reports that at the annual frequency 1980-2011, the correlation of growth rates is greater than 0.85 for California, less than 0.40 for North Dakota, Nebraska and Louisiana.

The timeliness of the coincident indices is achieved by relying upon high frequency labor market statistics; these indicators are subject to revision, so in turn the coincident index is subject to revisions. As Novak (2013) observes, for the one month change, the one month revisions are fairly modest, 0.034%

[5] Applying the Bry-Boschan (1971) method, which mimics the NBER judgmental approach (described further in Section 3.2), to the national coincident index, Flora (2016a) identifies recessions and expansions similar in dating to those obtained by the NBER.

(std dev = 0.05%) relative average growth of 3% per annum (or 0.25% per month). Benchmark revisions are larger – around 0.94%, with roughly the same standard deviation.[6]

The main factor in revisions to the coincident indices is the revisions to nonfarm payroll employment, followed by the unemployment rate. The combination of the revisions to the two variables account for roughly three-quarters of the coincident variable revisions (Novak, 2013: 9).[7]

3. Coherence between Indicators

3.1 Correlation and Comovement

Which indicator is best for tracking economic growth of a particular state? Suppose for instance one is interested in the broadest measure of economic activity, namely GDP. In Table 1, we present the correlation coefficients between real GDP and personal income (deflated by the national personal consumption expenditure deflator), nonfarm payroll employment, civilian employment and the Philadelphia Fed's coincident indices, over the 2005-2017 period. For the latter three variables, the monthly data have been aggregated to the quarterly frequency by simple averaging.

Since these macroeconomic series appear, like most other macroeconomic series, to be nonstationary (see Chinn, 1991), we first difference all the variables in their logged form, rendering

[6] !2 month changes are on the order of one third of the one month changes. The results pertain to the 2005-2011 period.

[7] The Philadelphia Fed also constructs leading indices, based on the Stock-Watson methodology. These indices incorporate the variables in the coincident indices, augmented by state-level housing permits (1 to 4 units), state initial unemployment insurance claims, delivery times from the Institute for Supply Management (ISM) manufacturing survey, and the interest rate spread between the 10-year Treasury bond and the 3-month Treasury bill. A VAR is used to construct 6-month forecasted growth rates of the coincident indices. See Federal Reserve Bank of Philadelphia (2018) and Crone (2000).

them stationary. These series can then be interpreted as quarter-on-quarter growth rates of the variables.[8]

The correlations are, as one might expect, largely positive. In many instances, they are also statistically significant. This outcome means that most indicators that analysts rely upon – personal income, employment, and coincident indices – do correlate with GDP.

It's particularly reassuring that coincident indices, which aim to track GDP, is often positively and significantly correlated with GDP in most cases (72%). In one case, GDP is negatively correlated (albeit not significantly so) with the coincident index: Delaware.

There are notable cases where none of the measures correlate significantly and positively with GDP: Alaska, Louisiana, Maryland, New Mexico, and Virginia. Of these cases, some are unsurprising. For instance, Alaska and New Mexico have large primary sectors, so that GDP is likely to be affected by weather and other global factors.

Interestingly, New York's GDP is only correlated with income, but not with, for instance coincident index.[9] To some extent, this makes sense the greater New York City economy and financial services dominate the state, it is perhaps not completely unexpected that the only positive correlation is with personal income.

Table 2 presents, in a fashion analogous to Table 1, the regression coefficients between GDP and these variables, with GDP as the dependent variable. A similar pattern of statistical significance for

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[8] We also examined the correlations and regression coefficients for fourth differenced series, using the 4th quarter of each year. These results are reported in Appendix 2.

[9] Connecticut, Delaware, and New York do not exhibit a significant coincident index-GDP correlation; they are also states in which the economies have a high proportion of finance, so the coincident indices might not be particularly useful in tracking (Flora, 2016b).

regression coefficients is obtained. The non-significant regression coefficients are largely associated with states with non-significant correlations in Table 1.

The coefficients in Table 2 are more readily interpretable than those in Table, 1, which are unitless. Take California: a one percentage point acceleration in the coincident index growth rate is associated with a 0.59 percentage point acceleration in GDP growth. Figure 9 summarizes the economic magnitude of the links.

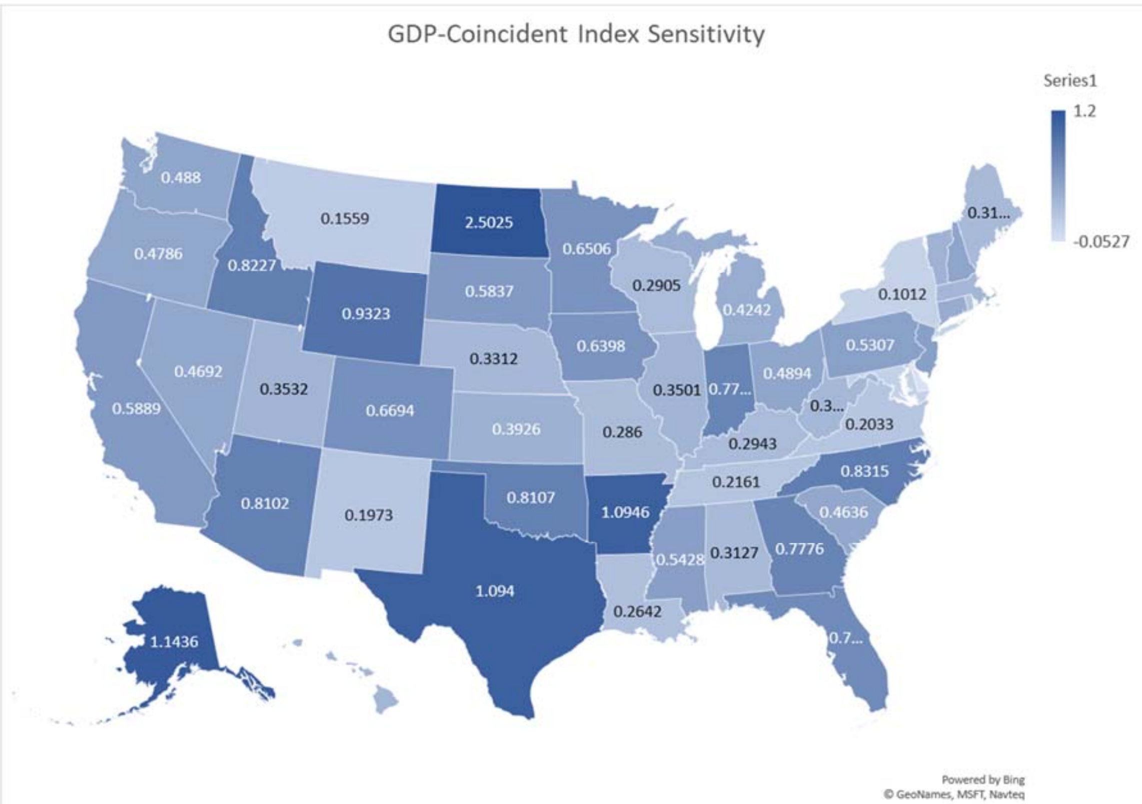

Figure 9: Sensitivity of GDP growth to Coincident Index growth, quarter-on-quarter.

For California, nonfarm payroll employment growth is associated with a 0.85 percentage point acceleration in GDP growth; a similar acceleration in civilian employment growth is associated with a 1.02 percentage point acceleration in GDP.

3.2 Business Cycles and Turning Points

Whether the economy is expanding or contracting is perhaps of equal importance to policymakers. In the parlance of business cycle analysis, is the economy in a recovery or a recession. This requires that one be able to determine peaks and troughs in economic activity. Contrary to a popular rule-of-thumb, a recession is not two consecutive quarters of negative growth. Rather, according to the NBER (2010), "A recession is a period between a peak and a trough, and an expansion is a period between a trough and a peak. During a recession, a significant decline in economic activity spreads across the economy and can last from a few months to more than a year. Similarly, during an expansion, economic activity rises substantially, spreads across the economy, and usually lasts for several years." The typical measures to determine the dating of these cycles include real GDP, real income, employment, industrial production, and wholesale-retail sales.

We do not have access to some of these variables at the state level, but we do have access to several, as well as one proxy measure, in the form of the Philadelphia Fed's coincident index.[10] We can examine how looking at peaks and troughs literally leads to determinations of business cycles, with particular reference to the most recent recession.

Figure 10.1 displays the national counterparts to the variables we've just reviewed in Section 3.1, along with the peaks and troughs for each of the series. Dark arrows denote the peaks, color coded to each series, while light arrows denote corresponding troughs, for the series as reported in May 2018.

[10] Diebold and Rudebusch (1996) proposed the use of coincident index turning points as a means of formalizing the NBER's narrative approach to business cycle dating.

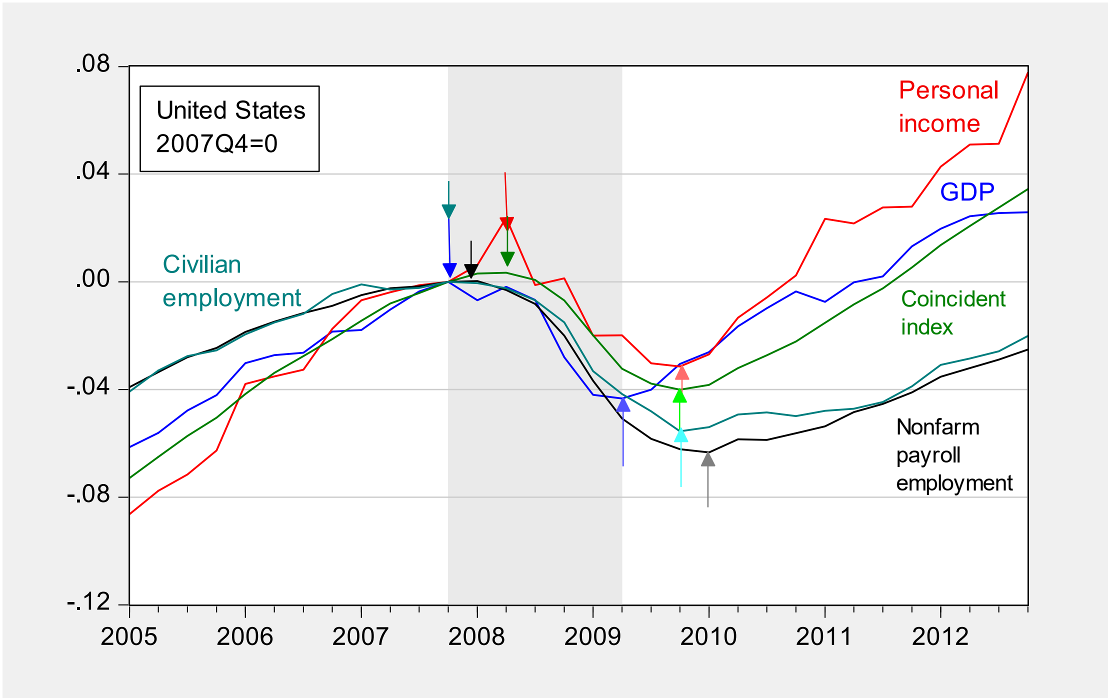

Figure 10.1: US Real GDP (blue), real personal income (red), coincident index (green), nonfarm payroll employment (black) and civilian employment (teal), all in logs, normalized to 2007Q4=0. NBER defined national recession dates shaded gray.

Notice that three of the indicators peak very close to the NBER defined peak at 2007Q4. Personal income and the coincident index peak a couple quarters later than the NBER peak.[11]

The GDP trough matches the NBER trough, while the other indicators are substantially later. Payroll employment is three quarters later. One point to keep in mind is that the NBER made the trough determination in September of 2010, over a year after the trough. The data series have been revised since that determination was made, and hence the troughs might have looked different in earlier vintages of these series.

Now consider two states: a large, diversified economy (California), and a smaller, resource rich economy (Wyoming). The corresponding depictions appear in Figures 10.2 and 10.3.

[11] The NBER uses personal income *excluding government transfers*; we use total personal income.

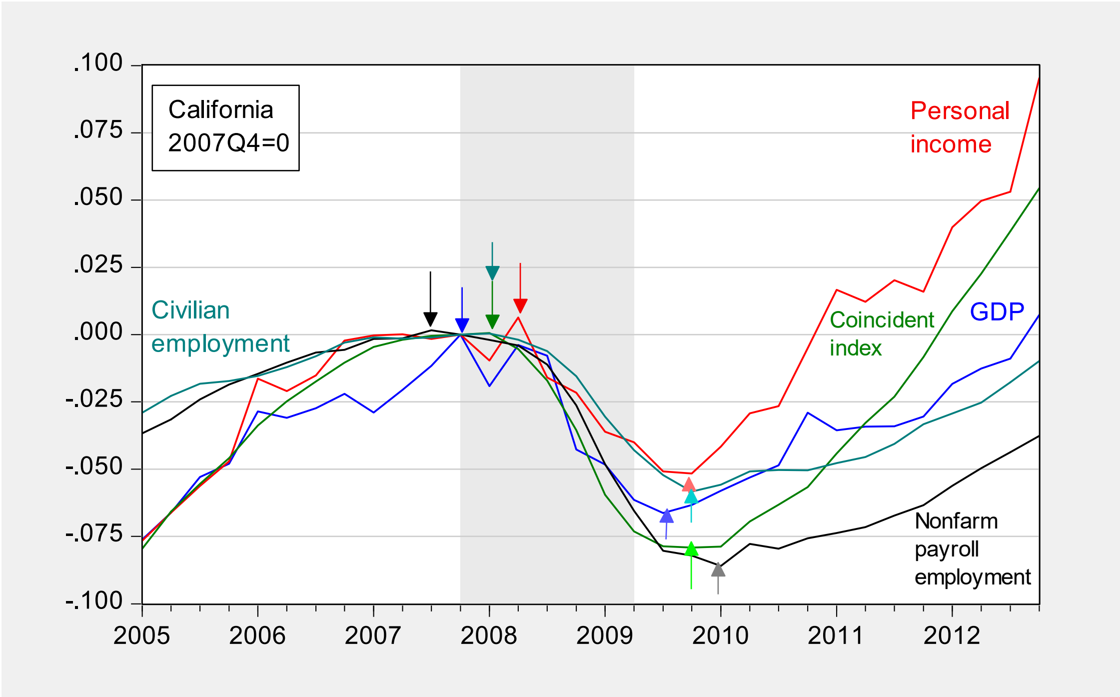

Figure 10.2: California Real GDP (blue), real personal income (red), coincident index (green), nonfarm payroll employment (black) and civilian employment (teal), all in logs, normalized to 2007Q4=0. NBER defined national recession dates shaded gray.

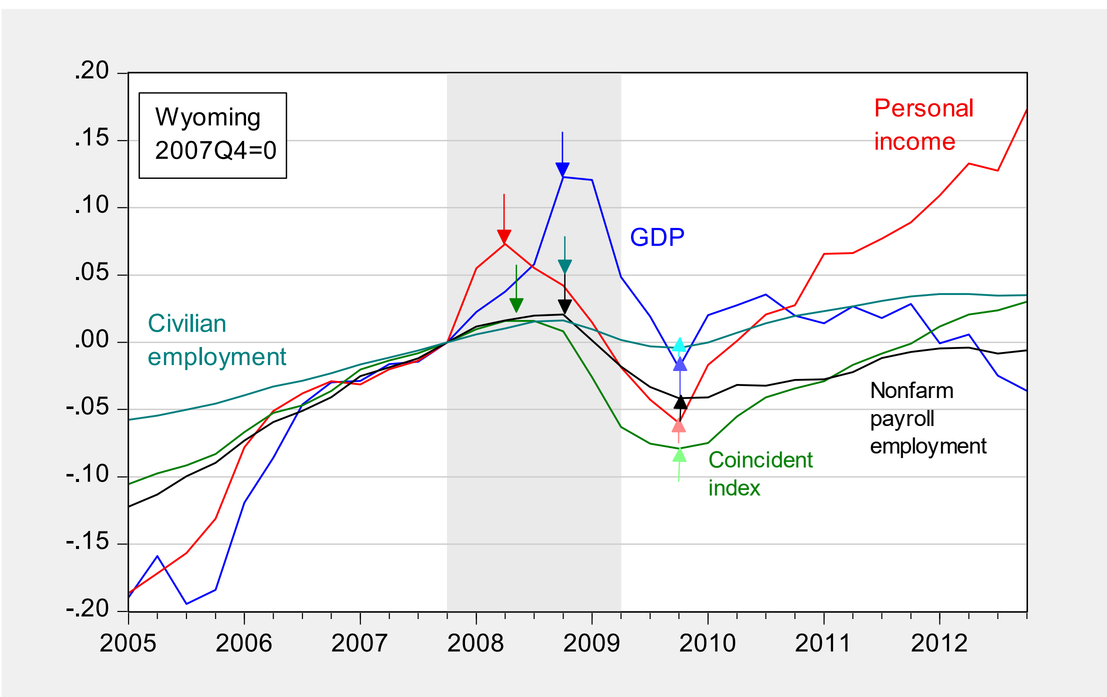

Figure 10.3: Wyoming Real GDP (blue), real personal income (red), coincident index (green), nonfarm payroll employment (black) and civilian employment (teal), all in logs, normalized to 2007Q4=0. NBER defined national recession dates shaded gray.

For California, the indicators indicate a peak somewhere between 2007Q3-2008Q2, and a trough somewhere near 2009Q3-2010Q1. Hence, there is rough agreement between the measures. For Wyoming, there is – despite the disparate post-recession trends – similar coherence. The peak is identified as between 2008Q2-2008Q4. Interestingly, all the indicators agree on a trough in 2009Q4. Hence, these measures seem to agree on turning points, perhaps even more than they do in terms of growth trends.

We have used a simple visual method of picking peaks. A more formal approach, associated with Bry and Boschen (1971), involves the implementation of an algorithm to search for local maxima and minima using a sample window of set length, subject to a constraint on a minimum length of a cycle. This algorithm is acknowledged to mimic the NBER Business Cycle Dating Committee dates. Brown (2015) uses this method in his analysis of state level cycles as applied to the Philadelphia Fed's coincident indices.[12]

Ahking (2016) examines the concordance between cycles identified using a quarterly version of the Bry and Boschen algorithm to both the coincident indices (converted to quarterly frequency) and the state GDP series, over the 2005-2013 period. He finds that the algorithm typically identifies peak and one trough for a given state using the coincident indices, while multiple cycles are often identified using the GDP series: Alaska, Louisiana, Mississippi, Montana, New Mexico, West Virginia, and Wyoming. This is an

[12] Owyang, Piger and Wall (2005) and more recently Brown also use a Markov switching methodology associated with Hamilton (1978) to define "expansion" and "contraction" growth states. Since this approach requires only lagged data (Bry-Boschan requires both leading and lagging data), it might be more useful for inferring turning points in real time. However, to my knowledge, there has been no assessment of forecasting ability using either methodology using real-time data.

unsurprising finding, once one considers the relatively "jagged" characteristic of the GDP series, as compared to the coincident indices.

Ahking calculates a formal concordance index, which indicates the proportion of time during which both indicators – coincident index and GDP – are both in expansion or both in contraction. Ahking finds that for the US as a whole, the proportion is 89% (vs. expected 72%). For California, it's 61% (vs. expected 52%), Wyoming, it's 69% (vs. expected 60%). The relative maximum is Nevada at 78% (vs expected 51%), and the relative minimum is Louisiana at 36% (vs expected 46%).

The foregoing discussion has focused on determining turning points after the fact, much like the NBER determines business cycle peaks and troughs months or even years after the respective events. For policymakers, what is also of great importance is determining turning points *in real time*. The time span of quarterly state GDP is too short to effectively evaluate the characteristics of GDP over different vintages.[13]

4. An Application: Did the Kansas Tax Cut Spur Growth?

In 2012, the Kansas state legislature passed, and Governor Brownback signed, legislation which would reduce the tax rate on pass-through corporations to zero, and reduce other income tax rates, with full implementation taking place in calendar year 2014. At the time, the governor asserted that the tax program would act like a "shot of adrenaline" (Brownback, 2012). The outstanding question then is whether output rose as a consequence of this measure.

This is a difficult question to answer comprehensively, as it would require a fully fleshed out model, with explicit stances taken on causality, and the channels whereby which the tax measure

[13] Prototype series were released in 2014, and the first official series were released in 2015 (Cao, et al., 2016).

affected economic behavior. With minimal data available at a high frequency, and in a timely manner, what can one do?

A reasonable approach is to see if output differed from what it otherwise would have been in the case of no tax cut. That requires the construction of a counterfactual, taking a stand on what is kept constant and what is not. Using quarterly data on GDP places a constraint on the parameterization possible, given the low degrees of freedom, a constraint that could be relaxed using coincident index data or employment data. However, in order to illustrate how to conduct analysis with severe constraints, we use quarterly Kansas GDP data.

We construct a counterfactual GDP series by using data from 2005-2013 period (2005 is the beginning of the quarterly state GDP series, 2013 is just before the tax plan is fully implemented.) We consider candidate explanatory variables to US GDP and commodity prices. The relevant series are plotted in Figures 11 and 12.

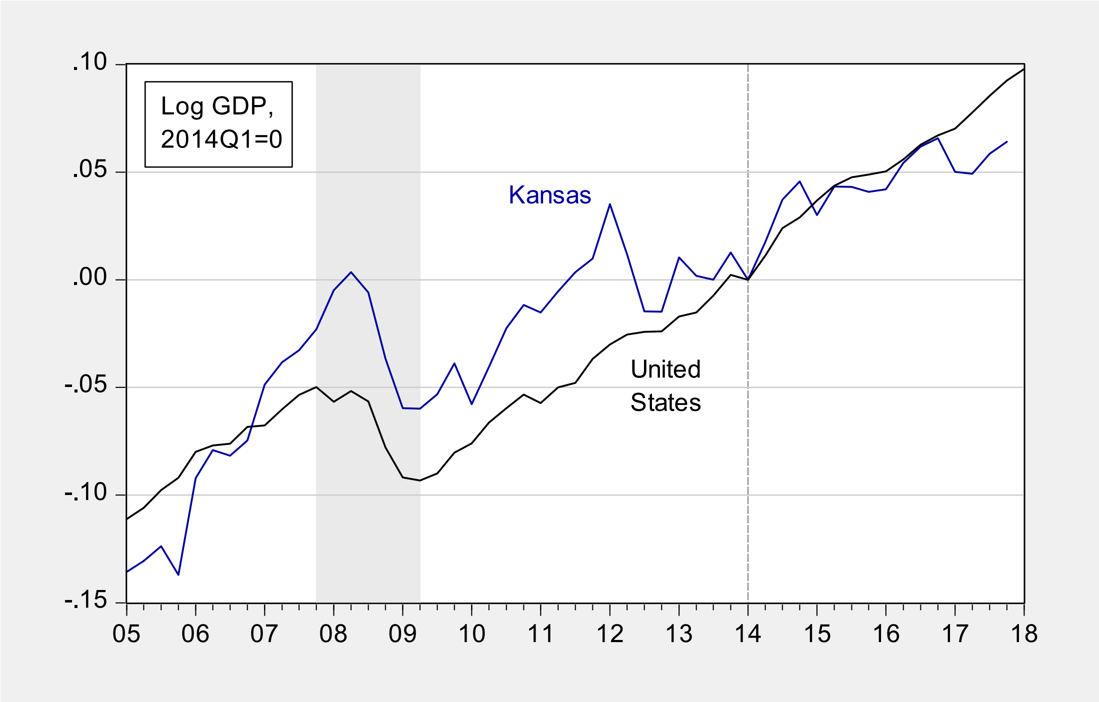

Figure 11: Log Kansas GDP (blue) and US GDP (black), in Ch.2009$, normalized 2014Q1=0. NBER defined recession dates shaded gray.

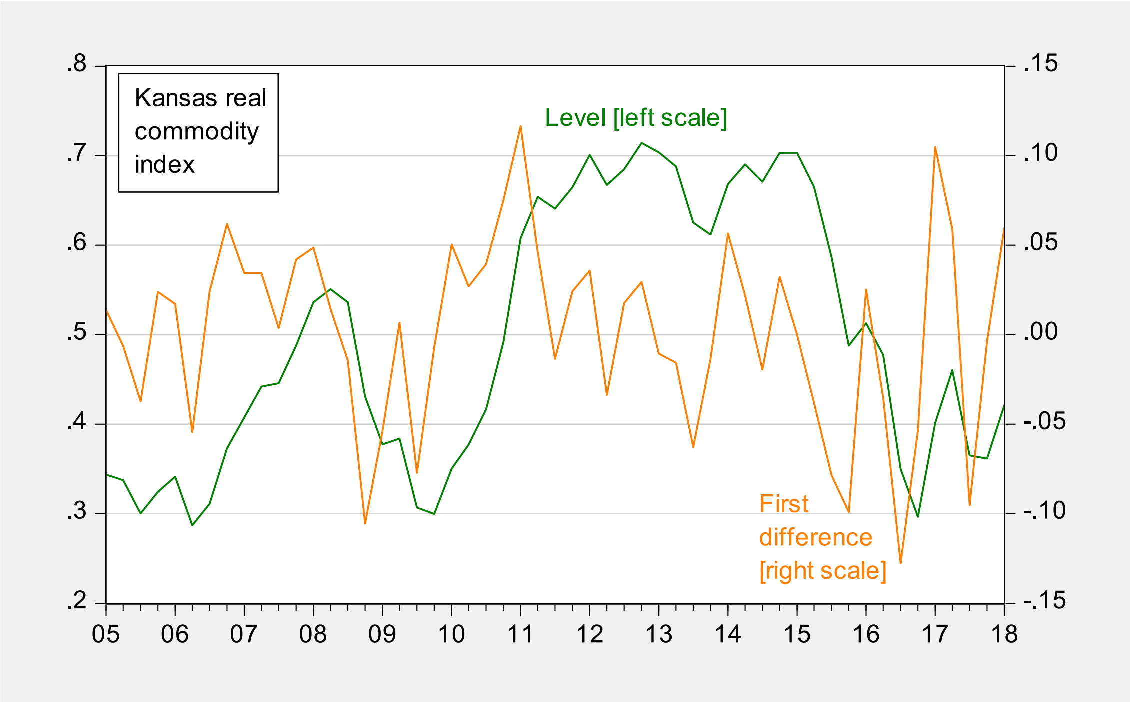

Figure 12: Real commodity price index for Kansas (green, left scale), and first difference (orange, right scale).

A traditional approach would be to estimate a log linear relationship between the candidate variables, possibly augmented with a deterministic time trend to account for trend factors. However, it is likely that the time series under consideration are nonstationary, i.e., do not possess a population mean. A random walk series is a prominent example of a nonstationary series of a particular type, namely integrated of order 1 [i.e., I(1)]. This means it takes one first-differencing in order to render the series stationary, so that conventional methods of statistical inference can be applied.

We apply the Elliott-Rothenberg-Stock unit root test, and both GDP series fail to reject the null hypothesis that these series are I(1). The commodity price index (borderline) fails to reject a unit root null hypothesis as well. That means that arguably all three variables are integrated.

If two or moreseries exhibit a long run relationship in levels, we call those series "cointegrated". We posit such a relationship for Kansas and US GDP[14]; hence use an error correction model which is consistent with the existence of such a long run relationship between Kansas real GDP and US real GDP. We augment the specification with a variable that measures real commodity prices in Kansas, and assume that it only has short run effects[15]. The regression equation estimated is:

$$\Delta y_t^{KS} = \underset{(0.735)}{0.478} - \underset{(0.076)}{\mathbf{0.190}} y_{t-1}^{KS} + \underset{(0.107)}{\mathbf{0.182}} y_{t-1}^{US} + \underset{(0.235)}{\mathbf{0.945}} \Delta y_t^{US} + \underset{(0.048)}{\mathbf{0.123}} \Delta c_{t-1} + u_t$$

Adj-R2 = 0.42, SER = 0.0124, N = 35, Sample 2005Q2-2013Q4. DW = 2.04, Breusch-Godfrey Serial Correlation LM Test = 1.19 [p-value = 0.32]. Bold face denotes statistical significance at 10% msl, using HAC robust standard errors. The Box-Ljung q-statistics for up to 8 lags does not reject the null of no serial correlation.

[14] We apply the standard Johansen multivariate maximum likelihood test over the entire sample for three variables, and find no evidence of cointegration at conventional levels. For the US and Kansas GDP, we reject the no cointegration null at the 16% level using the trace test (using 1 lag of first differences, no trend in cointegrating vector). The cointegrating vector is [-1 0.80], which implies a long run elasticity not dissimilar to the 0.90 obtained using the ECM. Hence, we proceed assuming cointegration.

[15] The real commodity price is a divisia index, calculated as a weighted average of growth rates of CPI deflated cattle, wheat and corn prices, with weights equal to 2/3, 1/6, and 1/6 respectively. These weights roughly match their importance of the top three agricultural commodities produced in Kansas.

Where y denotes log real GDP, and c is the real commodity price index for Kansas, and Δ denotes a first difference operator.

The estimates indicate that Kansas GDP closes the gap between Kansas and national GDP at about 19% per quarter, or about 37% per year. Over the long run, a one percent increase in US GDP is associated with a 0.92 percent increase in Kansas GDP (0.92 = 0.182/0.190). In a given period, when US *growth* accelerates by 1%, Kansas GDP growth accelerates by 0.95%. Finally, an acceleration of commodity real price growth causes a 0.1% acceleration in Kansas GDP growth in the subsequent quarter.

Using this ECM to dynamically forecast out of sample in an ex post historical simulation (i.e., using realized values of US GDP, and the commodity variable), we obtain the forecast shown in Figure 13.

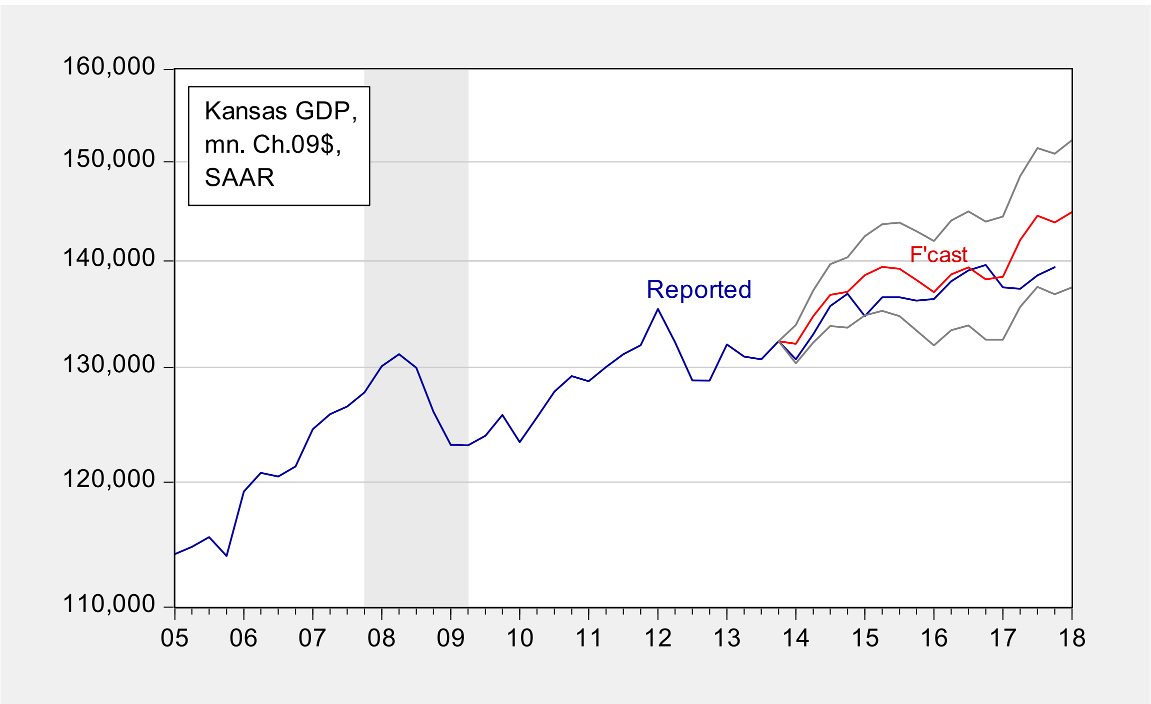

Figure 13: Kansas GDP as reported (blue), and forecast (red), and 60% prediction interval (gray lines), all in millions Ch.2009$, SAAR. NBER defined recession dates shaded gray.

We find that actual Kansas GDP is at times far below predicted (5.9 billion Ch.2009$ SAAR, or 4.2%, as of 2017Q3). In other words, given the evolution of US GDP and commodity prices, and the historical correlations that held until 2013Q4, economic output was below expected. However, given the imprecision of the estimates, the shortfall is not statistically significant, even at the 40% level.

The interpretation of the results are made more challenging by the fact that the prediction interval accounts only for the sampling error associated with estimating the coefficients. We assume that we "know" the correct specification for the model in constructing the interval. Perhaps, more importantly for the quarterly GDP series, the GDP estimates are subject to sometimes large revisions. When those revisions occur, estimates of the actual and where the actual level of GDP stands relative to the estimated counterfactual will change. In other words, one must always be cautious about overinterpreting the results. However, additional confidence can be gained if one cross-checks the results – for instance evaluating whether similar results are obtained using coincident indicesor employment measures.

5. Conclusions

Until recently, the analysis of trends in state level economic activity has been hampered by a dearth of consistent, cross-state macroeconomic data, on a higher than annual frequency. Labor market indicators cover only one aspect of economic activity, and (for the household series) are subject to large measurement error.

For some time, the Philadelphia Fed's coincident and leading indices served to partly fill the gap. However, these indices are themselves based largely on labor market variables. The advent of quarterly GDP for the states has been a boon to those who want to track economic activity, broadly defined.

However, the fairly short span of data available (starting in 2005) and the sometimes substantial revisions in the series suggest that one would not wish to rely solely on the GDP statistics.

In fact, one would want to consult a number of indicators in assessing the outlook for a given state's economy, and the impact of policies, be they fiscal, regulatory or other, on economic activity. In general, however, outside observers are better armed to assess conditions than they were in the past.

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Table 1: Correlation between the first difference in log between state GDP and other indicators				
State	**Income**	**Nonfarm Employment**	**Civilian Employment**	**Coincident Index**
Alabama	0.2363*	0.4364***	0.4567***	0.5301***
Alaska	0.0203	0.1162	0.1187	0.1755
Arizona	0.5402***	0.7277***	0.5865***	0.6851***
Arkansas	0.1871	0.3433**	0.2498*	0.2078
California	0.5933***	0.5648***	0.5006***	0.5317***
Colorado	0.4388***	0.4490***	0.3357**	0.3964***
Connecticut	0.5619***	0.3167**	0.1757	0.2245
Delaware	0.4053***	-0.0401	0.0484	-0.0259
Florida	0.2929**	0.6477***	0.5049***	0.6004***
Georgia	0.1872	0.4891***	0.5305***	0.5176***
Hawaii	0.1408	0.3691***	0.3803***	0.3779***
Idaho	0.2231	0.5139***	0.4663***	0.4356***
Illinois	0.2667*	0.3291**	0.3258**	0.3804***
Indiana	0.1484	0.5144***	0.3685***	0.5033***
Iowa	0.2893**	0.2691*	0.0835	0.3636***
Kansas	0.6062***	0.3526**	0.1324	0.3292**
Kentucky	0.2255	0.4453***	0.2674*	0.4014***
Louisiana	0.0896	0.1061	0.2242	0.1682
Maine	0.1620	0.2070	0.1824	0.2911**
Maryland	0.1537	0.1707	0.1539	0.1662
Massachusetts	0.3985***	0.2024	0.2164	0.3654***
Michigan	0.5134***	0.7070***	0.6282***	0.6408***
Minnesota	0.3396**	0.3067**	0.2404*	0.3865***
Mississippi	0.2838**	0.4114***	0.1240	0.2213
Missouri	0.3794***	0.2416*	0.0377	0.2168
Montana	0.3265**	0.3358**	0.3355**	0.2517*
Nebraska	0.4153***	-0.1544	-0.0519	0.0835
Nevada	0.5137***	0.6775***	0.5843***	0.5579***
New Hampshire	0.2531*	0.1085	0.1337	0.1594
New Jersey	0.0092	0.4853***	0.2859**	0.3883***
New Mexico	0.2006	0.1418	0.1244	0.1303
New York	0.6609***	-0.0094	0.0557	0.0597
North Carolina	0.2840**	0.4614***	0.4297***	0.5092***
North Dakota	0.7672***	0.7682***	0.5904***	0.7155***
Ohio	0.1711	0.4677***	0.4081***	0.4950***
Oklahoma	0.5659***	0.4564***	0.2864**	0.3588***
Oregon	0.3584***	0.2253	0.4593***	0.2580*
Pennsylvania	0.3797***	0.3833***	0.2452*	0.3962***
Rhode Island	0.3167**	0.3248**	0.2912**	0.2490*
South Carolina	0.2052	0.4788***	0.4671***	0.5155***
South Dakota	0.6425***	0.2159	0.0781	0.1728
Tennessee	0.1210	0.5057***	0.3226**	0.3452**
Texas	0.3484**	0.4719***	0.2524*	0.4971***
Utah	0.4576***	0.4916***	0.5103***	0.3174**
Vermont	0.1494	0.2635*	0.1268	0.3125**
Virginia	0.0055	0.3074**	0.1293	0.1738

Washington	0.3056**	0.4613***	0.4793***	0.3955***
West Virginia	0.3139**	0.3518**	0.0707	0.2335*
Wisconsin	0.1830	0.3586***	0.1958	0.3746***
Wyoming	0.3433**	0.5110***	0.4581***	0.4021***

Significance levels: * p<.1, ** p<.05, *** p<.01

Table 2: Regressions of the first difference in log between state GDP and other indicators				
State	**Income**	**Nonfarm Emp**	**Civilian Emp**	**Coincident Index**
Alabama	0.1983**	0.6554**	0.4462***	0.3127***
Alaska	0.0317	0.5800	1.1300	1.1436
Arizona	0.5176***	1.0337***	1.2107***	0.8102***
Arkansas	0.2070	1.2050**	0.7123*	1.0946
California	0.4319***	0.8478***	1.0242***	0.5889***
Colorado	0.3480***	0.7354***	0.6705**	0.6694***
Connecticut	0.6688***	1.0233	0.6258	0.4297
Delaware	0.6989*	-0.1664	0.1572	-0.0527
Florida	0.2317	0.9087***	0.7804***	0.7171***
Georgia	0.1512	0.7306***	0.5838***	0.7776***
Hawaii	0.1601	0.5928**	0.5424**	0.3463**
Idaho	0.2205	0.7524***	0.9845***	0.8227**
Illinois	0.2420	0.6112	0.5398*	0.3501**
Indiana	0.2063	1.0643***	0.7266	0.7711***
Iowa	0.3121*	0.8564*	0.2916	0.6398***
Kansas	0.5751***	1.0827**	0.8160	0.3926**
Kentucky	0.2581	0.9572***	0.7207*	0.2943***
Louisiana	0.0837	0.1222	0.4359*	0.2642
Maine	0.1722	0.5104	0.4040	0.3117**
Maryland	0.1436	0.3124	0.3932	0.1066
Massachusetts	0.3708***	0.4715*	0.6019	0.3371***
Michigan	0.5552**	1.2873***	1.2593***	0.4242***
Minnesota	0.3864*	0.8004*	1.1779	0.6506**
Mississippi	0.2689***	0.9495***	0.1381	0.5428
Missouri	0.3157	0.5211	0.0906	0.2860
Montana	0.2966*	0.6229***	0.7947***	0.1559*
Nebraska	0.3998***	-0.6482	-0.3548	0.3312
Nevada	0.4636**	0.8446***	1.0300***	0.4692***
New Hampshire	0.3526**	0.5342	0.9850	0.4894
New Jersey	0.0089	1.0033***	0.7271	0.5403**
New Mexico	0.2010	0.3199	0.3581	0.1973
New York	0.6355***	-0.0312	0.1742	0.1012
North Carolina	0.1747	0.7045**	0.7289**	0.8315***
North Dakota	0.7620***	1.9194***	3.0436***	2.5025***
Ohio	0.1766	0.8241**	0.7992**	0.4894**
Oklahoma	0.6083***	1.7569***	1.4533***	0.8107***
Oregon	0.4749**	0.4735**	1.0454***	0.4786**
Pennsylvania	0.3824*	0.9942**	0.5639	0.5307**
Rhode Island	0.3339*	0.6850***	0.6373***	0.2145***
South Carolina	0.1758	0.6528***	0.8509***	0.4636***
South Dakota	0.8708***	1.4206	0.6340	0.5837
Tennessee	0.1207	0.7261***	0.4063*	0.2161**
Texas	0.2191*	0.8765***	0.7831	1.0940***
Utah	0.3585***	0.6913**	0.8114***	0.3532
Vermont	0.1630	0.7116*	0.5105	0.3709***
Virginia	0.0036	0.4719**	0.1917	0.2033
Washington	0.2740	0.8563***	1.0921***	0.4880**

West Virginia	0.3760*	0.9707***	0.2050	0.3294**
Wisconsin	0.1602	0.7055*	0.4527	0.2905*
Wyoming	0.4237*	1.5120***	2.6941***	0.9323**

Significance levels: * p<.1, ** p<.05, *** p<.01

Appendix 1
Data Sources

- State level employment data: There are two surveys that are the basis for the employment data, both at the monthly frequency; the establishment survey and the household survey. The former is the basis for the nonfarm payroll employment series, while the latter is the basis for the civilian employment series. Source: http://www.bls.gov/eag/. Data used for the establishment survey is from the April 23, 2018 revision. Data used for the household survey is from the May 4, 2018 revision.
- State level employment census data: the Quarterly Census of Employment and Wages (QCEW) provides monthly data on all establishment employment, not on a seasonally adjusted basis. Data used is from the March 8, 2018 release that includes data through Q3 of 2017.
- State level coincident indices: Summary measure of economic activity, monthly frequency. https://www.philadelphiafed.org/research-and-data/regional-economy/indexes/coincident/. Data used is from the March 2018 report, released on May 3, 2018.
- Quarterly state level GDP: http://www.bea.gov/iTable/iTable.cfm?reqid=70&step=1&isuri=1&acrdn=1#reqid=70&step=1&isuri=1. Data used is from the May 4, 2018 release.
- State personal income: personal income, quarterly frequency. In paper, deflated by national level personal consumption expenditure deflator. Source: http://www.bea.gov/iTable/iTable.cfm?reqid=70&step=1&isuri=1&acrdn=1#reqid=70&step=1&isuri=1. Data used is from the March 22, 2018 release.
- Data used in Section 4
    - Quarterly US data. National estimate of GDP.

Real commodity prices for Kansas. Divisia index of prices of cattle, wheat and corn, deflated by CPI-all, and weighted 2/3, 1/6, 1/6, respectively. Commodity prices from FRED.

Appendix 2
Results for Fourth Differenced Quarterly Data

Table A1: Correlation between the fourth difference in log between state GDP and other indicators				
State	**Income**	**Nonfarm Employment**	**Civilian Employment**	**Coincident Index**
Alabama	0.3987	0.6034**	0.7925***	0.7394***
Alaska	0.6885**	0.5242*	0.7505***	0.2397
Arizona	0.7258***	0.8555***	0.7138***	0.8421***
Arkansas	0.0624	0.4023	0.4117	0.3360
California	0.6719**	0.8427***	0.7786***	0.8340***
Colorado	0.6528**	0.6925**	0.6641**	0.6928**
Connecticut	0.2329	0.0538	0.0546	0.0611
Delaware	0.2000	0.0396	0.0863	0.1183
Florida	0.6090**	0.8413***	0.6666**	0.7455***
Georgia	0.5828**	0.7373***	0.7271***	0.7616***
Hawaii	0.2978	0.6377**	0.6964**	0.6545**
Idaho	0.4666	0.7573***	0.7002**	0.7429***
Illinois	0.3074	0.3871	0.6817**	0.4953
Indiana	-0.0205	0.4545	0.4714	0.5915**
Iowa	0.1381	0.1349	0.1193	0.2857
Kansas	0.3565	0.4203	0.3445	0.3147
Kentucky	-0.0687	0.4152	0.2617	0.4054
Louisiana	0.0570	-0.2311	-0.0201	0.0494
Maine	0.0898	0.1302	0.1744	0.3528
Maryland	-0.0311	0.0131	0.1599	0.0872
Massachusetts	0.4726	0.4066	0.3794	0.6419**
Michigan	0.6002**	0.8495***	0.7933***	0.8033***
Minnesota	0.0938	0.3703	0.4080	0.3991
Mississippi	0.4325	0.5978**	0.5153*	0.5553*
Missouri	0.2380	0.4601	0.0435	0.1839
Montana	0.4465	0.5684*	0.5268*	0.3675
Nebraska	0.2970	-0.3161	-0.2953	-0.1083
Nevada	0.7219***	0.8326***	0.7498***	0.7402***
New Hampshire	0.4219	0.0572	0.0094	0.1822
New Jersey	0.3587	0.8567***	0.5308*	0.8023***
New Mexico	0.6109**	0.3768	0.4623	0.2533
New York	0.2837	-0.4758	-0.5007*	-0.2779
North Carolina	0.0627	0.6641**	0.6699**	0.6440**
North Dakota	0.9302***	0.8866***	0.7316***	0.7673***
Ohio	0.3144	0.5698*	0.5220*	0.6337**
Oklahoma	0.8884***	0.8803***	0.7772***	0.8143***
Oregon	0.1806	0.2704	0.6792**	0.2234
Pennsylvania	0.1843	0.4547	0.2429	0.5851**
Rhode Island	0.2906	0.4471	0.4827	0.4712
South Carolina	0.2437	0.6497**	0.6102**	0.6935**
South Dakota	0.3255	-0.3497	-0.4209	-0.2612
Tennessee	0.5208*	0.8200***	0.6879**	0.8967***
Texas	0.7063**	0.7834***	0.7060**	0.8066***
Utah	0.5884**	0.6967**	0.6647**	0.5571**
Vermont	-0.0603	0.1964	0.1757	0.2238
Virginia	-0.0357	0.0562	-0.0342	0.0964

Washington	0.4805	0.7216***	0.6741**	0.5804**
West Virginia	0.4408	0.5329*	0.2056	0.3732
Wisconsin	-0.2475	0.1028	0.1780	0.1908
Wyoming	0.6187**	0.8242***	0.6990**	0.6787**

Significance levels: * p<.1, ** p<.05, *** p<.01. HAC robust standard errors

Table A2: Regressions of the Fourth difference in log between state GDP and other indicators				
State	**Income**	**Nonfarm Employment**	**Civilian Employment**	**Coincident Index**
Alabama	0.3582	0.5447**	0.5126***	0.2628**
Alaska	0.9071***	1.9912**	5.0549***	1.0039
Arizona	0.7662***	0.9229***	1.0498***	0.6887***
Arkansas	0.0514	0.8315	0.6747**	0.9595
California	0.4886**	0.8558***	1.0286***	0.5992***
Colorado	0.4301***	0.7320**	0.8144***	0.7307***
Connecticut	0.2697	0.1014	0.0998	0.0577
Delaware	0.3420	0.0704	0.1060	0.0931
Florida	0.4999*	0.9132**	0.8103*	0.6822**
Georgia	0.6089	0.8679*	0.7627**	0.8814**
Hawaii	0.3146	0.6661**	0.6631**	0.3734**
Idaho	0.4559	0.8000***	0.9909***	0.9411***
Illinois	0.2200	0.4267	0.6338*	0.2712
Indiana	-0.0268	0.6199	0.5428	0.5756*
Iowa	0.1459	0.2871	0.2774	0.3607
Kansas	0.2695	0.6616*	0.9963	0.1934
Kentucky	-0.0716	0.5186	0.3396	0.1651
Louisiana	0.0426	-0.2882	-0.0265	0.0915
Maine	0.1063	0.2099	0.2306	0.2348
Maryland	-0.0210	0.0138	0.2032	0.0274
Massachusetts	0.3739**	0.5356	0.5092	0.2952*
Michigan	0.7605***	1.1277***	1.1034***	0.4320***
Minnesota	0.0714	0.5005*	0.8947*	0.3539
Mississippi	0.4664	0.5961**	0.2669	0.5916**
Missouri	0.1201	0.3708	0.0369	0.0963
Montana	0.3452	0.7757**	0.8027**	0.1486
Nebraska	0.2326	-0.7099	-0.9794	-0.2385
Nevada	0.6827**	0.8894***	1.0627***	0.4765***
New Hampshire	0.4320	0.1356	0.0321	0.2822
New Jersey	0.2184	0.7471***	0.5536**	0.4242***
New Mexico	0.5680*	0.5445	0.7890***	0.2544
New York	0.2442	-0.8825	-0.8398*	-0.2414
North Carolina	0.0339	0.5288***	0.6033***	0.5768***
North Dakota	0.9574***	1.8368***	3.3132***	2.8347***
Ohio	0.3887	0.7392	0.7223	0.4719*
Oklahoma	0.6786***	1.8836***	2.2763***	1.0306***
Oregon	0.2126	0.3660**	0.9864**	0.3118*
Pennsylvania	0.1170	0.4997	0.2068*	0.3096*
Rhode Island	0.2673	0.5159	0.5410*	0.2072*
South Carolina	0.2365	0.6545*	0.7576*	0.4862**
South Dakota	0.2475	-0.9209*	-1.0276**	-0.3461
Tennessee	0.4801	0.7076**	0.4817**	0.3917***
Texas	0.4368***	0.9910***	1.6291***	1.2043***
Utah	0.4774*	0.7690*	0.7888*	0.5478*
Vermont	-0.0657	0.3466	0.5069	0.1987
Virginia	-0.0156	0.0459	-0.0246	0.0524

Washington	0.3854*	1.0044**	1.0865***	0.5062**
West Virginia	0.5412	1.3751***	0.4375	0.3987***
Wisconsin	-0.1723	0.0948	0.1775	0.0712
Wyoming	0.7816**	2.0177***	3.1867**	1.4222***

Significance levels: * p<.1, ** p<.05, *** p<.01. HAC robust standard errors