DISCUSSION PAPER SERIES

No. 7069

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INTERNATIONAL MACROECONOMICS

Centre for Economic Policy Research

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ISSN 0265-8003

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Discussion Paper No. 7069
December 2008

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CEPR Discussion Paper No. 7069

December 2008

ABSTRACT

The U.S. Business Cycle, 1867-1995: A Dynamic Factor Approach*

This paper reexamines U.S. business cycle volatility since 1867. We employ dynamic factor analysis as an alternative to reconstructed national accounts. We find a remarkable volatility increase across World War I, which is reversed after World War II. While we can generate evidence of postwar moderation relative to pre-1914, this evidence is not robust to structural change, implemented by time-varying factor loadings. However, we find moderation in the nominal series. Moreover, we reproduce the standard moderation since the 1980s. Our estimates confirm the NIPA data also for the 1930s but support alternative estimates of Kuznets (1952) for World War II.

JEL Classification: C43, E32, N11 and N12
Keywords: dynamic factor analysis, u.s. business cycle and volatility

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Submitted 24 November 2008

*Thanks are due to Pooyan Amir Ahmadi, Barry Eichengreen, Peter Lindert, Bartosz Maćkowiak, Marco del Negro, Wolfgang Reichmuth, Christina Romer, Harald Uhlig and participants in several conferences and seminars. Financial support from Deutsche Forschungsge-meinschaft through SFB 649 “Economic Risk” at Humboldt University of Berlin is gratefully acknowledged. Martin Uebele acknowledges financial support from DekaBank. Samad Sarferaz and Martin Uebele acknowledge financial support from the Marie Curie Research Training Network “Unifying the European Experience". Samad Sarferaz thanks the University of Zurich and the European University Institute in Florence for their hospitality.

1 Introduction

Measuring the American business cycle in the long run has been the subject matter of much debate. While there is broad agreement on the business cycle turning points, the issue of volatility is still not fully resolved, as different available estimates yield contradictory results. How severe were the key recessions other than the Great Depression of the 1930s, that is, the recessions of the mid 1880s, of 1907, and of 1920/21? Was the wartime boom of the early 1940s really so strong? And has the U.S. business cycle become more moderate since World War II, not just with respect to the interwar period but also compared to the prewar years?

Researchers have disagreed on the severity of the downturn after World War I as well as on the other two questions. Following Burns (1960), DeLong and Summers (1986) argued that business fluctuations after World War II were more moderate than before World War I, and certainly during the interwar period. This view was challenged in a series of papers by Romer (1986, 1988), who argued that postwar stabilization relative to the decades before World War I was an artifact of the historical output and unemployment data.

Given the lack of reliable aggregate series for the decades before 1929 when the official National Income and Product Accounts (NIPA) set in, existing evidence was based on Historical National Account (HNA) estimates. Most of the debate evolved around two rivaling such series and their implications for U.S. business cycle volatility since the 19th century. Balke and Gordon (1986, 1989) modified a popular GNP series originating from the Commerce Department, for which they produced a widely used quarterly interpolation. The high volatility of this series before World War I, compared to the rather moderate fluctuations of postwar GNP, is what shaped conventional wisdom in the 1980s. Romer (1986, 1988) challenged this view based on a revision of the alternative series of Kendrick (1961), which she argued was less prone to spurious volatility.[1] Her results implied that there was no postwar moderation relative to the pre-World War I years. However, her own calculations have been criticized for depending on assumptions which are not empirically testable given the lack of historical GNP data, see Lebergott (1986). Following Kim and Nelson (1999a), McConnell and Perez-Quiros (2000), Blanchard and Simon (2001), and Stock and Watson (2002), research on the stabilization of the U.S. business cycle has therefore focused mostly on moderation within the postwar period itself (see Jaimovich and Siu (2008), Gali and Gambetti (2008) and Giannone, Lenza, and Reichlin (2008) for recent contributions to this debate).

The present paper offers an alternative but complementary approach to measuring the volatility of the U.S. business cycle in the very long run. We draw on the growing literature on diffusion indices (using a term of Stock and Watson (1998)) of economic activity, which are distilled from a large panel of disaggregate time series using dynamic factor analysis (DFA). Stock and Watson (1991) developed an unobserved component model for disaggregate series representing the U.S. postwar economy which reliably replicates the NBER's business cycle turning points.[2] Fac-

[1]Both the Commerce and the Kendrick series are related to earlier work by Kuznets (1941, 1946), see Romer (1988) for a discussion.

[2] Stock and Watson (1998) employed 170 series in a forecast of U.S. postwar industrial produc-

tor models have become popular as an alternative to national accounts because they aggregate a large amount of disaggregate information and are less affected by data revisions than national accounts. The same issues loom large with historical data. Disaggregate series are often abundant for historical periods, but usually do not match national accounting categories well, and the information needed for proper aggregation is incomplete. As a consequence, proxies have to be used, which can be controversial as mentioned above. The DFA approach replaces the questionable aggregation techniques used in the construction of HNAs with a statistical aggregator. Series that would be of limited use in reconstructing HNAs can now be exploited for their business cycle indicator characteristics, i.e. their contribution to the common component. To our knowledge, this approach was first applied in the context of presenting an alternative to HNA estimates by Gerlach and Gerlach-Kristen (2005) for Switzerland between the 1880s and the Great Depression of the 1930s. Sarferaz and Uebele (2007) employ a Bayesian dynamic factor model to obtain an index of economic activity for 19th century Germany, comparing it to different rivaling HNA-based chronologies. The present paper extends this approach to the historical application of macroeconomic diffusion indices with time-varying factor loadings, following the methodology set out by Del Negro and Otrok (2003, 2008). This helps to capture structural change, which is important if long time spans are to be covered[3].

In this paper, we study the evolution of U.S. business cycle volatility over time in two exercises. The first exercise covers the full sample from 1867 to 1995. In the second exercise, we examine the change in volatility across World War I to 1929. Results are compared to the HNA reconstructions of GDP for the pre-1929 era by Balke and Gordon (1989) and Romer (1989). In the first exercise, we include 53 time series that are constructed on an unchanged methodological basis. For the second exercise, we employ a wider panel of 98 such series. Data are taken from the Historical Statistics of the U.S., see Carter, Gartner, Haines, Olmstead, Sutch, and Wright (2006), as well as the NBER's Macrohistory Database, which itself dates back to the business cycle project of Burns and Mitchell (1946).

Our findings suggest no overall postwar moderation relative to the pre-World War I period. We introduce identifying restrictions to study sectoral indices separately and find our results confirmed, except for agriculture and services. This is informative about existing HNA estimates, where the proper way to include these two sectors was disputed. We also specify nominal factors and find evidence in favor of postwar moderation in the nominal series compared to pre-1914. At the same time, the 1970s were more volatile than the period of the classical Gold Standard before World War I. We replicate the standard evidence on reduced volatility after the 1980s (see e.g. Cogley and Sargent (2005) Primiceri (2005), Gali and Gambetti (2008), and Giannone, Lenza, and Reichlin (2008)). We also obtain new results on

tion and consumer prices.

[3]Romer (1991) did estimate a factor model for 38 individual U.S. output series to examine the behavior of the individual factor loadings for relevant subperiods. Her results reject constant factor loadings, a finding supported by out results. In examining the volatility of the factor itself and introducing time-varying factor loadings explicitly, our approach can be viewed as a straightforward extension of hers.

the 1921 slump, as well as the wartime boom during World War II.

The remainder of the paper is structured as follows. The next section briefly sketches the Bayesian factor model. Section 3, divided up in several subsections, presents the evidence. Section 4 concludes. Data and technical details are discussed in the appendix.

2 A Bayesian Dynamic Factor Model

2.1 The Model

Dynamic factor models in the vein of Sargent and Sims (1977), Geweke (1977) and Stock and Watson (1989) assume that a panel dataset can be characterized by a latent common component that captures the comovements of the cross section, and a variable-specific idiosyncratic component. These models imply that economic activity is driven by a small number of latent driving forces, which can be revealed by estimation of the dynamic factors. A Bayesian approach to dynamic factor analysis is provided by Otrok and Whiteman (1998) and Kim and Nelson (1999b), amongst others. Del Negro and Otrok (2003) generalize the estimation procedure to dynamic factor models with time-varying parameters. Our own approach closely follows their methodology.

Our panel of data Y_t , spanning a cross section of N series and an observation period of length T, is described by the following observation equation:

$$Y_t = \Lambda_t f_t + U_t \tag{1}$$

where f_t represents a 1×1 latent factor, while Λ_t is a $N \times 1$ coefficient vector linking the common factor to the i-th variable at time t, and U_t is an $N \times 1$ vector of variable-specific idiosyncratic components. The latent factor captures the common dynamics of the dataset and is our primary object of interest.[4]. We assume that the factor evolves according to an AR(q) process:

$$f_t = \varphi_1 f_{t-1} + \ldots + \varphi_q f_{t-q} + \nu_t \tag{2}$$

with $\nu_t \sim \mathcal{N}(0, \sigma_\nu^2)$. The idiosyncratic components U_t are assumed to follow an AR(p) process:

$$U_t = \Theta_1 U_{t-1} + \ldots + \Theta_p U_{t-p} + \chi_t \tag{3}$$

where $\Theta_1, \ldots, \Theta_p$ are $N \times N$ diagonal matrices and $\chi_t \sim \mathcal{N}(0_{N\times1}, \Omega_\chi)$ with

$$\Omega_\chi = \begin{bmatrix} \sigma_{1,\chi}^2 & 0 & \cdots & 0 \\ 0 & \sigma_{2,\chi}^2 & \vdots & \vdots \\ \vdots & \cdots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma_{N,\chi}^2 \end{bmatrix}$$

[4] Generalization to several factors is straightforward.

The factor loadings or coefficients on the factor in equation (1), Λ_t, are assumed to be either constant or (in the time-varying model) follow a driftless random walk, as in del Negro and Otrok (2003, 2008):

$$\Lambda_t = \mathcal{I}_N \Lambda_{t-1} + \epsilon_t \tag{4}$$

where $\mathcal{I}_N$ is a $N \times N$ identity matrix and $\epsilon_t \sim \mathcal{N}(0_{N\times 1}, \Omega_\epsilon)$ with

$$\Omega_\epsilon = \begin{bmatrix} \sigma^2_{1,\epsilon} & 0 & \cdots & 0 \\ 0 & \sigma^2_{2,\epsilon} & \vdots & \vdots \\ \vdots & \cdots & \ddots & 0 \\ 0 & \cdots & 0 & \sigma^2_{N,\epsilon} \end{bmatrix}$$

and where the disturbances χ_t and ϵ_t are independent of each other.

The above setup specifies an exact factor model in the sense that it assigns all comovement between the series to the (single) factor. This identifying assumption arises quite naturally in our context, where we use comovement to obtain a measure of aggregate volatility. The setup also restricts the innovations to the transition equations for the factor, the factor loadings, and the idiosyncratic component to be i.i.d. Generalizations to stochastic volatility have been introduced in a VAR context by Cogley and Sargent (2005) and Primiceri (2005), and in a dynamic factor model by Del Negro and Otrok (2008). Not allowing for stochastic volatility in our setup is again an identifying assumption. It has the effect of assigning all volatility to either the factor or the model parameters, with priors chosen such as to map volatility at business cycle frequencies into the factors, and slower time variation into the factor loadings.

The dynamic factor in this model is identified up to a scaling constant and a sign restriction. We deal with scale indeterminacy by normalizing the standard deviation of the factor innovations to $\sigma_\nu = 1$. The sign indeterminacy of the factor loadings Λ_t and the factor f_t is resolved by a sign convention, i.e. by restricting one of the factor loadings to be positive (see Geweke and Zhou (1996)). Neither operation involves loss in generality.

2.2 Priors

Before proceeding to the estimation of the system, we specify prior assumptions. These priors are informative and have a substantive interpretation in terms of our research question, especially with regard to time variation in the parameters. We adopt priors for four groups of parameters of the above system. These are, in turn, the parameters in the factor equation (2), the parameters in equation (3) governing the law of motion of the idiosyncratic component, the parameters in the law of motion of the factor loadings (4) and the parameters in the observation equation (1).

For the AR parameters $\varphi_1, \varphi_2, \ldots, \varphi_q$ of the factor equation, we specify the following prior:

$$\varphi^{prior} \sim \mathcal{N}(\underline{\varphi}, \underline{V}_\varphi)$$

where $\underline{\varphi} = 0_{q\times 1}$ and

$$\underline{V}_{\varphi} = \tau_1 \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & \frac{1}{2} & \vdots & \vdots \\ \vdots & \cdots & \ddots & 0 \\ 0 & \cdots & 0 & \frac{1}{q} \end{bmatrix}$$

Analogously, for the AR parameters $\Theta_1, \Theta_2, \ldots, \Theta_p$ of the law of motion of the idiosyncratic components, we specify the following prior:

$$\theta^{prior} \sim \mathcal{N}(\underline{\theta}, \underline{V}_{\theta})$$

where $\underline{\theta} = 0_{p\times 1}$ and

$$\underline{V}_{\theta} = \tau_2 \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & \frac{1}{2} & \vdots & \vdots \\ \vdots & \cdots & \ddots & 0 \\ 0 & \cdots & 0 & \frac{1}{p} \end{bmatrix}$$

We choose $\tau_1 = 0.2$ and $\tau_2 = 1$. Both priors are shrinkage priors that punish more distant lags on the autoregressive terms, in the spirit of Doan, Litterman, and Sims (1984). This is implemented by progressively decreasing the uncertainty about the mean prior belief that the parameters are zero as lag length increases. Related priors are employed in Kose, Otrok and Whiteman (2003) and del Negro and Otrok (2008).

For the variances of the disturbances in χ_t, we specified the following prior:

$$\sigma_{\chi}^{2\ prior} \sim \mathcal{IG}\left(\frac{\alpha_{\chi}}{2}, \frac{\delta_{\chi}}{2}\right)$$

We choose $\alpha_{\chi} = 6$ and $\delta_{\chi} = 0.001$, which implies a fairly loose prior. $\mathcal{IG}$ denotes the inverted gamma distribution.

For the factor loadings, we distinguish two cases. With constant factor loadings (disregarding structural change), the relevant prior for each individual factor loading is:

$$\lambda^{prior} \sim \mathcal{N}(\underline{\lambda}, \underline{V}_{\lambda})$$

where $\underline{\lambda} = 0$ and $\underline{V}_{\lambda} = 100$.

With time-varying factor loadings, for each of the variances of the disturbances in ϵ_t the prior is:

$$\sigma_{\epsilon}^{2\ prior} \sim \mathcal{IG}\left(\frac{\alpha_{\epsilon}}{2}, \frac{\delta_{\epsilon}}{2}\right)$$

We chose α_{ϵ} and δ_{ϵ} so as to capture longer term structural variation by changing factor loadings, while volatility at the relevant business cycle frequencies is assigned to movements in the factors.[5]

[5]We work with $\alpha_{\epsilon} = 100$ and $\delta_{\epsilon} = 1$, which generated a good fit for the postwar data.

2.3 Estimation

We estimate the model in Bayesian fashion via the Gibbs sampling approach. This procedure enables the researcher to draw from nonstandard distributions by splitting them up into several blocks of standard conditional distributions. In our case, the estimation procedure is subdivided into three blocks: First, the parameters of the model c, φ, θ_r for $s = 1, \ldots, q$ and $r = 1, \ldots, p$ are calculated. Second, conditional on the estimated values of the first block, the factor f_t is computed. Finally, conditional on the results of the previous blocks we estimate the factor loadings. After the estimation of the third block, we start the next iteration step again at the first block by conditioning on the last iteration step. [6] These iterations have the Markov property: as the number of steps increases, the conditional posterior distributions of the parameters and the factor converge to their marginal posterior distributions at an exponential rate (see Geman and Geman (1984)).

3 Empirical Results

Estimates were obtained for lag lengths $p = 1, q = 8$, taking 30,000 draws and discarding the first 9,000 as burn-in. Specifications with constant and time-varying factor loadings are reported alongside each other. Convergence of the Gibbs sampler was checked by varying the starting values and comparing the results. All series were detrended using the Hodrick-Prescott filter with the (6.25) parameters suggested by Ravn and Uhlig (2002) for business cycle frequencies, and were subsequently standardized.[7]

3.1 The U.S. Business Cycle in the Long Run

Figure 1 is our representation of the American business cycle between 1867 and 1995. It shows a one-factor model of aggregate economic activity, obtained from 53 consistent time series available for that period. The official NIPA series of GDP starting in 1929 and a GDP estimate of Romer (1989) for 1867-1929 are shown for comparison. The factor is calibrated to the standard deviation of NIPA from its HP (6.25) trend for 1946-1995.

Figure 1 about here.

As the Figure shows, the factor captures the business cycle turning points in GDP quite well. This is true for both the postwar period and the historical business cycles and the 19th century (see Miron and Romer (1990), Davis (2004) and Davis, Hanes, and Rhode (2004) for details on the chronology.)

Differences with the GDP data emerge around the World Wars. The recession of 1920/21 comes out more strongly than in the GDP estimates of Romer (1988) and, to a lesser extent, Balke and Gordon (1989). Also, our factor does not show

[6]See the appendix for a more detailed description of the estimation procedure.

[7]We also tried Christiano and Fitzgerald (2003) and Baxter and King (1999) filters as well as first-differencing, with little change in results. Data sources are listed in Appendix Table A-1.

the peak in the NIPA estimate of GDP during World War II. We will discuss these results in more detail below.

The factor shown in Figure 1 is based on conservative assumptions about the degree of time variation in the factor loadings. As we are interested in historical volatility comparisons, our approach is to restrict time variation in factors loadings to low-frequency structural changes, such that volatility at the relevant business cycle frequencies is captured by the factors themselves. Figure 2 shows the factor loadings for our 53 series under our preferred conservative prior against a more diffuse alternative. As can be seen, the tight prior allows for smooth changes in the factor loadings while suppressing volatility at business cycle frequencies. In contrast, cyclical components are present in the factor loadings under the loose prior, which would affect the volatility of the factor at the relevant frequencies and is therefore discarded.

Figure 2 about here

The factor in Figure 1, representing aggregate activity, is our yardstick for intertemporal comparisons of U.S. business cycle volatility. Table 1 compares volatility in the post-World War II period to the pre-World War I era. Results are provided for both constant and time-varying factor loadings. The GDP estimates of Romer (1989) and Balke and Gordon (1986, 1989) , designed to extend the NIPA data on GDP backwards from 1929, provide the relevant comparison for the period prior to World War I.

Table 1 about here

In Table 1, the volatility of all data is calibrated to NIPA for the postwar period. For the prewar period, Balke/Gordon's GDP estimate is more volatile than postwar GNP, indicating postwar moderation in the U.S. business cycle. Romer's (1989) estimate of pre-1914 GDP is less volatile, which suggests no postwar moderation relative to the prewar business cycle.

Table 1 reports two versions of our factor model, one with constant, the other with time varying factor loadings. For constant factor loadings, the factor indicates no change in postwar volatility relative to the prewar period. In this, it reproduces Romer's (1989, 1991) results. For time-varying factor loadings, the prewar business cycle becomes even less volatile than in Romer's estimate. This would imply that the U.S. postwar business cycle was probably more, not less volatile than before World War I.

Yet we can also reproduce Balke/Gordon's (1986, 1989) postwar moderation result. To this end, we focus on a subset of the data that is closest to their GDP estimate. Under constant factor loadings, a factor for non-agricultural real series (see Table 1) exhibits substantial postwar moderation in volatility, close to the reduction implied by the Balke and Gordon (1986, 1989) data. Indeed, their estimate (and the Commerce series of GDP on which it is based) relies heavily on industrial output, as pointed out by Romer (1986, 1989). The comovement of these series, assuming constant weights, generates moderation across the World Wars also in our factor model. However, this result is not robust to allowing time variation in weights. Under time varying factor loadings as shown in Table 1, postwar volatility is again higher than before World War I.

While in both cases, postwar volatility comes out higher relative to pre-1914 if time-varying factor loadings are assumed, this is not always the case. A counterexample is provided by agricultural production. Under constant factor loadings, a factor model of agriculture shows a strong increase in volatility across the World Wars. Time varying factor loadings yield the opposite result, making the postwar agricultural cycle seem strongly muted relative to the pre-World War I period (see Table 1). We find this to be reassuring, as increasing agricultural productivity would allow farmers to shift away from the cultivation of weather-dependent and disease-prone crops, thus helping to reduce the volatility of agricultural output. Such a shift would imply changes in the composition of output, which are better captured by time-varying factor loadings.

We obtain a similar effect for the transport and communication series in our dataset. Constant factor loadings would suggest an almost 40% increase in volatility of a suitably identified factor across the World Wars. Including such series in a physical product estimate of pre-war GDP, as suggested by Romer (1989), will therefore tend to lower or eliminate the postwar moderation that is implicit in the indiustrial output series. The lower volatility of Romer's own, broader GDP estimate relative to the physical-output estimate underlying the Balke and Gordon (1986) series is thus reflected in our sectoral results. However, once we allow the factor loadings to vary over time, the volatility increase in these non-production series almost disappears.

The above sectoral factors contribute to an explanation of why the Balke/Gordon and Romer estimates of pre-war GDP differ in volatility. While the former relies more strongly on industrial output, the latter gives higher weight to agriculture and services. Given the low pre-war volatility of the two latter sectors, a broader aggregate obtained under constant weights will necessarily reduce or close the volatility gap that exists in the Balke/Gordon series.

However, introducing time varying factor weights shows that the sectoral discrepancies between pre- and postwar volatility are not the only effect, and not even the dominant one. What matters more is the near-inevitable assumption of constant weights in existing Historical National Accounts for the U.S. Romer (1988, 1989) attempted to overcome this constraint by backward-extrapolating postwar trends in weighing schemes to the pre-World War I estimates. We obtain similar and more pronounced results by allowing slow time variation in the factor loadings, which constitute the weighing scheme of the factor model. As soon as time variation is introduced, a statistical aggregator of economic activity suggests less volatile business cycles in the 19th century than existing estimates, and hence no moderation in the U.S. business cycle across the World Wars.

Similar index problems are present in the long run volatility comparison of the nominal series. A factor obtained from these series under constant factor loadings is essentially a Laspeyres price index. As Table 1 bears out, this index would indicate increased nominal volatility in the postwar period. This would be in line with Balke and Gordon (1989), who presented a novel GNP deflator which was substantially less volatile before World War I than previous deflators, thus challenging an older conventional wisdom about high price volatility under the Gold Standard.

However, this finding is again not robust to introducing time variation in the factor loadings. If, as before, we allow for a moderate degree of time variation on the factor loadings, there is postwar moderation relative to pre-1914 in the nominal series. This would lend renewed support to traditional views of price level volatility under the Gold Standard.

Drawing the results of this section together, our principal findings appear to depend on whether or not we account for structural change. If we assume time-invariant factor loadings, our results suggest postwar moderation in real economic activity but not in the nominal series. This would underscore the results of Balke and Gordon (1989), in spite of using a rather different technique. However, as soon as time variation in the factor loadings is permitted, we obtain the opposite result of postwar moderation in the nominal series, but not in overall economic activity. This appears to be consistent with claims of Romer (1989), who argued for the need to account for changing weighting patterns. Our own approach toward time-varying index weights is quite different from hers but seems to confirm her principal conclusions.[8]

3.2 The U.S. Business Cycle Across World War I

As a robustness check for the above results, this section focuses on changes in business cycle volatility across World War I. Comparing the pre-1914 years with the interwar period has several advantages. First, it allows us to use a substantially larger dataset of 98 series covering the period from 1867 to 1939 on a consistent basis. Second, choosing the interwar years as the reference period also eliminates possible bias in representing postwar volatility. The GNP data in Balke and Gordon (1986, 1989) bear out a substantial increase in volatility across World War I, while the estimates by Romer (1988) suggested the increase was much weaker. The discrepancy between their findings is partly related to the recession of 1920/21, which is rather mild in Romer's data. In contrast, Balke and Gordon (1989) report a more severe slump.

In the following, we repeat the above exercise for the subperiods from 1867 to 1929 and 1867 to 1939. For the pre- and interwar period, we have a wider dataset of 98 series at hand. To maintain comparability, we will also reestimate the factor model with the narrower dataset of 53 series employed in the previous section. As the results of the previous section were shown to depend so much on time variation in the aggregation procedure, we will again examine constant and time varying loadings alongside each other. The volatility of both factors is calibrated to that of the Balke and Gordon series, obtained as the standard deviation of the cyclical component from a HP(6,25) filter. Figure 4 shows the cyclical components in both series alongside the factors (thick solid lines) from 1867-1929. Comparisons with

[8]See Appendix Table A-2 for an overview of results by decades.

Romer's (1989) real GNP measure are shown in the upper panel, while the lower does the same with the Balke and Gordon (1989) GNP estimate.

Figure 4 here.

This comparison yields two insights. For the pre-1913 period, the Romer estimate of GDP seems to be more in line with our factor estimates than the Balke and Gordon estimate. For the period from 1914 to 1929, our factors are closer to the Balke and Gordon series than to the Romer estimate. This is particularly true for the slump of 1921, which according to the Balke and Gordon data pushed the cyclical component of output down by almost 9%, compared to only 5% in the Romer (1989) estimate. We also note that the factor indicates a major upturn in the second half of the 1920s, an effect that is missing from both of the rivaling GDP estimates. This evidence would, however, be consistent with a reconstructed index of indsutrial production by Miron and Romer (1990).

Table 2 here.

Table 2 makes the outcome more explicit. The upper panel shows the standard deviation of the cyclical components in Romer's and Balke and Gordon's GNP estimates for subperiods up until 1929. As both series are spliced to the official NIPA series of GDP in 1929, the standard deviations of both series for 1930 to 1939 are identical. As before, the standard deviation of the factor estimates needs to be calibrated.

To do this, we choose three different approaches, each estimating the factors over a different time span. Under the first approach, the factor is estimated for the whole period to 1995 and its volatility calibrated to NIPA for 1946-1995. This is the same strategy adopted in Table 1 above. Results are shown in the second panel of Table 2. The second approach is to estimate the factor only from 1867 to 1929, and to calibrate to the cyclical component of the Balke and Gordon (1989) series. As we have more series available for this subperiods, we conduct this experiment twice, once for the same 53 series that are available through 1995, the second time for the wider dataset of 98 series. This strategy also underlies Figure 4. Results are shown in the center panel of Table 2. The third approach, shown in the lower panel of Table 2 is to estimate the factors from 1867 to 1939, and to calibrate to the standard deviation of NIPA for 1930 to 1939.

As the factor estimates are not recursive, truncation of the estimation period affects the results for all subperiods. Truncating to 1867-1929, which is the period of interest in this section, makes for an unbiased comparison of volatilities across World War I. Extending the estimation period to 1995, as in the upper panel, or to 1939, as in the lower panel, introduces potential bias, as any misrepresentation of volatility post-1929 might carry over to the factor estimate as a whole. On the other hand, estimating beyond 1929 permits calibrating the factors to the volatility of the official NIPA data. As a consequence, volatility in the pre-1929 years can be directly compared to volatility in the NIPA series for relevant subperiods.

Three results stand out from these robustness checks. First, the increase in factor volatility across World War I consistently comes out higher than in Romer's or even Balke and Gordon's GDP estimate (Table 2, last column). This result is robust to truncations of the estimation period, as well as to widening the database for the factor estimate from 53 to 98 series. It is also remarkably invariant to the choice between constant and time-varying factor loadings. The second main result is that pre-1914 volatility in the factor estimates is always lower than the Balke/Gordon estimate would suggest (Table 2, first column). For the most part, the factors even suggest lower business cycle volatility than implied by the Romer estimate. This effect also obtains in those factor estimates which are calibrated to NIPA, be it for the postwar period or for 1930 to 1939. In both cases, prewar volatility is close to the postwar level of volatility (of 2.01, see Table 1 above) and in many cases markedly lower. The third main result is that volatility during 1914 to 1929 (second column in Table 2) is consistently higher than estimated by Romer (1989), and is indeed close to or even higher than in the Balke and Gordon (1989) data.

This result has additional implications for evaluating the outcomes of the debate between Romer and Balke and Gordon. Under various robustness checks, we find there is no evidence of postwar moderation relative to the pre-1914 period. This would confirm a main point of Romer (1989). On the other hand, we also find quite strong evidence of a marked volatility increases across World War I. This in turn would confirm a result of Balke and Gordon (1989) against criticism by Romer (1988).

3.3 The US Business Cycle Across World War II

Discrepancies between output and income based estimates of GDP exist also from 1929 onwards, when the NIPA accounts set in. These official accounts are themselves a compromise, leaning toward the Commerce Department's earlier output series. For the years around World War II, there are again doubts about the volatility of this series. The alternative estimates by Kuznets (1961) and Kendrick (1961) that underlie much of Romer's (1986, 1988, 1989) GDP revisions for the pre-1929 period also show less volatility than NIPA for 1939 to 1945. These estimates also suggest a less pronounced increase in economic activity, as well as a different business cycle chronology.[9]

In the following, we zoom in on the years 1929 to 1949 and compare the official national accounting figures with the income-based estimate by Kuznets (1961).

Figure 5 here.

In Figure 5, the upper panel plots the factor against the official NIPA accounts. The income estimate of Kuznets (1961) is shown in the lower panel. Data are again detrended by a HP(6.25) filter.

[9]For the discussion see Kuznets (1945), Mitchell (1943), Nordhaus and Tobin (1972), and a review in Higgs (1992, p. 45).

The factor estimate shown in this figure is obtained from real 36 series, identical to the one in Table 1 above. Simple eye-balling quickly delivers the message: Until 1938 the business cycle turning points in the factor are very close to those of both NIPA and Kuznets' income estimate (in passing we note the earlier trough of the Great Depression implied by the factor). During the war, however, the factor tracks the Kuznets estimate much more closely than the Commerce series on which the wartime NIPA data are based. According to our factor estimate, increasing wartime production did hardly offset the fall in civilian activity. In 1945, the lower turning point was reached by both measures.

The official NIPA data convey a different impression: from the lower turning point in 1940 on, they suggest an unprecedented rise in real output until 1944 – almost at the end of the war and one year before the factor and Kuznets' aggregate have their lower turning point. From the peak of war production, the economy according to NIPA fell into a deep recession that lasted until 1949.

Search for deeper reasons for this discrepancy must be left for future work. Methodological differences in accounting for war output, as well as weighting issues in the construction of the deflator, may have played a role.[10] However, we note that the factor drawn from 36 real series in Figure 5 and the broader factor drawn from 53 series, 17 of them nominal, in Figure 1 above provide essentially the same result for World War II. This suggests that deflating procedures are not a likely candidate for explaining the differences between the Commerce series and the Kuznets estimaates of wartime output and income.

Summing up, World War II is the one period where our factor exhibits marked deviations from the official NIPA figures. The cyclical behavior of the factor appears to support Kuznets and others who called for a revision of the official historiography of the American business cycle during World War II.

4 Conclusions

Factor analysis of aggregate economic activity represents an appealing alternative and complement to Historical National Accounts whenever the data are incomplete or plagued by structural breaks in reporting. In this paper, we re-examined the volatility of historical business cycles in the U.S. since 1867 using a dynamic factor model. Based on a large set of disaggregate time series, we obtained factors representing both aggregate and sectoral activity in the U.S. economy, and employed them to compare volatility across World War I as well as in the long run.

Our main finding is that the business cycle prior to World War I may have even been less volatile than has previously been thought, and was quite plausibly no more volatile than the postwar business cycle. We also find pervasive evidence that the interwar years, in particular the period immediately following World War I, were more volatile than has been maintained in parts of the more recent literature. This would make the Great Depression of the early 1930s less of a historical singularity.

For the years surrounding World War II we find indications that the standard

[10]See Kuznets (1952) for further discussion and Carson (1975) for details on the debate.

figures for national output misrepresent the business cycle turning points, and that both the wartime boom and the postwar bust of the US economy may have been weaker than suggested by the official NIPA data in GDP. These findings confirm earlier results by Kuznets (1961) and Kendrick (1961).

As would be expected, many of our results derive from the analysis of time variation in factor loadings, the weights assigned to the various individual series in constructing the index of aggregate economic activity. To this end, we employed a Bayesian approach to factor analysis, iterating over the likelihood function by Gibbs sampling. Our approach nests both constant and time-varying factor loadings. We view slow time variation in the factor loadings as an effective way of dealing with the structural changes in the U.S. economy, a problem that is hard to deal with in HNA approaches. Our findings suggest that spurious volatility in national accounts of the U.S. business cycle is to a large extent the consequence of time-invariant weighing schemes that underlie much work in national accounting with historical data.

Our findings are closely related to earlier work by Romer (1986, 1988, 1989) and Balke and Gordon (1989), which was based on backward extrapolations of national accounts into the late 19th and early 20th century. Balke and Gordon (1989) concluded from one standard GDP estimate that the U.S. business cycle was markedly more moderate in the postwar period than before the Gold Standard. Based on a rivaling estimate and imposing time-varying weighing schemes, Romer (1988, 1989) found little evidence of such postwar moderation. However, which is the better estimate remained open, as there appeared to be no way to validate the underlying assumptions independently. Our approach can be viewed as an attempt to provide such a validation method.

The flexibility of our estimation approach allowed us to recast the debate in terms of our model. Keeping factor loadings constant and thus shutting down structural change, we were able to reproduce the postwar moderation result. The same result also obtained when limiting attention to a subset of series representing material goods production, close in spirit to the Commerce Series of GDP employed by Balke and Gordon (1989). On the other hand, when allowing for time varying factor loadings – and thus structural change –, our results were closer to Romer's (1989) and even more pronounced. Weaker but qualitatively similar results obtained when broadening the database to include other than material goods output. Hence, the identification assumptions used by these authors generate qualitatively similar results under a rather different methodology, a robustness property that we find remarkable. Given that the time varying model produces a better overall description of the postwar data and is also is more appealing on a priori grounds, we lean toward Romer's (1989) conclusion of no postwar moderation in the U.S. business cycle. However, time variation or a widening of the dataset do not in all cases explain the differences between the rivaling national account series. Our factor estimates invariably suggest a marked recession in 1920/21, which is borne out by the Commerce series in Balke and Gordon (1989) but not by the Kuznets/Kendrick series in Romer (1988, 1989) . Postwar moderation does, however, obtain in the nominal data. A nominal factor becomes less volatile in the postwar era relative to pre-1914 if factor loadings are allowed to vary. With factor loadings fixed, however, we again arrive at the result of Balke and Gordon (1989): less real postwar volatility, but substantially more nominal fluctuations.

Under a plausible set of assumptions, this paper has found no evidence of postwar moderation in the U.S. business cycle relative to the Classical Gold Standard of pre-1914, except for post-1980. Under the same assumptions, we obtained evidence for strong moderation in nominal volatility. This suggests that if postwar monetary policy played a stabilizing role, it did so mainly by reducing volatility in inflation rates.

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5 Appendix

5.1 Estimating the Parameters

In this section we condition on the factor f_t and the factor loadings Λ_t, in order to estimate the parameters of the model.[11] Because equation (1) is a set of N independent regressions with autoregressive error terms, it is possible to estimate $\Theta_1, \Theta_2, \ldots, \Theta_p$, Ω_χ and Ω_ϵ equation by equation. We rewrite equation (3) as:

$$u_i = X_{i,u}\theta_i + \chi_i \tag{5}$$

where $u_i = [u_{i,p+1}\ u_{i,p+2}\ \ldots\ u_{i,T}]'$ is $T - p \times 1$, $\theta_i = [\theta_{i,1}\ \theta_{i,2}\ \ldots\ \theta_{i,p}]'$, is $p \times 1$ and $\chi_i = [\chi_{i,p+1}\ \chi_{i,p+2}\ \ldots\ \chi_{i,T}]'$ is $T - p \times 1$ and

$$X_{i,u} = \begin{bmatrix} u_{i,p} & u_{i,p-1} & \cdots & u_{i,1} \\ u_{i,p+1} & u_{i,p} & \cdots & u_{i,2} \\ \vdots & \vdots & \vdots & \vdots \\ u_{i,T-1} & u_{i,T-2} & \cdots & u_{i,T-p} \end{bmatrix}$$

which is a $T - p \times p$ for $i = 1, 2, \ldots, N$.

Combining the priors described in section 2.2 with the likelihood function conditional on the initial observations we obtain the following posterior distributions.

The posterior of the AR-parameters of the idiosyncratic components is:

$$\theta_i \sim N(\overline{\theta_i}, \overline{V}_{i,\theta}) I_{S_\theta} \tag{6}$$

where

$$\overline{\theta_i} = \left(\underline{V}_\theta^{-1} + (\sigma_{i,\chi}^2)^{-1} X_{i,u}' X_{i,u}\right)^{-1} \left(\underline{V}_\theta^{-1}\underline{\theta} + (\sigma_{i,\chi}^2)^{-1} X_{i,u}' u_i\right)$$

and

$$\overline{V}_{i,\theta} = \left(\underline{V}_\theta^{-1} + (\sigma_{i,\chi}^2)^{-1} X_{i,u}' X_{i,u}\right)^{-1}.$$

where I_{S_θ} is an indicator function enforcing stationarity.

The posterior of the variance of the idiosyncratic component $\sigma_{i,\chi}$ is:

$$\sigma_{i,\chi}^2 \sim \mathcal{IG}\left(\frac{(T + \alpha_\chi)}{2}, \frac{((u_i - X_i\theta_i)'(u_i - X_i\theta_i) + \delta_\chi)}{2}\right) \tag{7}$$

The posterior of the variance of the factor loadings $\sigma_{i,\epsilon}$ is:

$$\sigma_{i,\epsilon}^2 \sim \mathcal{IG}\left(\frac{(T + \alpha_\epsilon)}{2}, \frac{((\Delta\lambda_i)'(\Delta\lambda_i) + \delta_\epsilon)}{2}\right) \tag{8}$$

where $\lambda_i = [\lambda_{i,1}\ \lambda_{i,2}\ \ldots\ \lambda_{i,T}]'$ and Δ is the first difference operator for this vector. To estimate the AR -parameters of the factor $\varphi_1, \varphi_2, \ldots, \varphi_q$ we find it useful to rewrite equation (2) as:

$$f = X_f\varphi + \nu \tag{9}$$

where $f = [f_{q+1}\ f_{q+2}\ \ldots\ f_T]'$ is $T - q \times 1$, $\varphi = [\varphi_1\ \varphi_2\ \ldots\ \varphi_q]'$ is $q \times 1$, $\nu = [\nu_{q+1}\ \nu_{q+2}\ \ldots\ \nu_T]'$ is $T - q \times 1$ and

[11] See also Chib (1993).

$$X_f = \begin{bmatrix} f_q & f_{q-1} & \cdots & f_1 \\ f_{q+1} & f_q & \cdots & f_2 \\ \vdots & \vdots & \vdots & \vdots \\ f_{T-1} & f_{T-2} & \cdots & f_{T-q} \end{bmatrix}$$

which is $T - q \times q$. Thus, the posterior of the AR-parameters of the factor is:

$$\varphi \sim N(\overline{\varphi}, \overline{V}_{\varphi}) I_{S_{\varphi}} \tag{10}$$

where

$$\overline{\varphi} = \left(\underline{V}_{\varphi}^{-1} + (X_f' X_f\right)^{-1} \left(\underline{V}_{\varphi}^{-1} \underline{\varphi} + (X_f' f\right)$$

and

$$\overline{V}_f = \left(\underline{V}_{\varphi}^{-1} + X_f' X_f\right)^{-1}.$$

where $I_{S_{\varphi}}$ is an indicator function enforcing stationarity.

To estimate the factor loadings, when they are assumed to be constant, we rewrite equation (1) as:

$$y_i^* = \lambda_i f^* + \chi \tag{11}$$

where $y_i^* = [(1-\theta(L)_i) y_{i,p+1} \; (1-\theta(L)_i) y_{i,p+2} \ldots \; (1-\theta(L)_i) y_{i,T}]'$ which is $T-p \times 1$ and $f^* = [(1-\theta(L)_i) f_{p+1} \; (1-\theta(L)_i) f_{p+2} \; \ldots \; (1-\theta(L)_i) f_T]'$, which is $T-p\times 1$ with $\theta(L)_i = (\theta_{i,1} + \theta_{i,2} + \cdots + \theta_{i,p})$ for $i = 1, 2, \ldots, N$. Thus, the posterior for the constant factor loadings is:

$$\lambda_i \sim N(\overline{\lambda_i}, \overline{V}_{i,\lambda}) \tag{12}$$

where

$$\overline{\lambda_i} = \left(\underline{V}_{\lambda}^{-1} + (\sigma_{i,\chi}^2)^{-1} f^{*\prime} f^*\right)^{-1} \left(\underline{V}_{\lambda}^{-1} \underline{\lambda} + (\sigma_{i,\chi}^2)^{-1} f^{*\prime} y_i^*\right)$$

and

$$\overline{V}_{i,\lambda} = \left(\underline{V}_{\lambda}^{-1} + (\sigma_{i,\chi}^2)^{-1} f^{*\prime} f^*\right)^{-1}.$$

5.2 Estimating the Latent Factor

To estimate the common latent factor we condition on the parameters of the model $\Xi \equiv (\varphi_1, \varphi_2, \ldots, \varphi_q, \Theta_1, \Theta_2, \ldots, \Theta_p)$ and the factor loadings Λ_t. We begin by quasi-differencing equation (1) and use it as our observation equation in the following state-space system:

$$Y_t^* = H_t F_t + \chi_t \tag{13}$$

where

$$Y_t^* = (\mathcal{I}_N - \Theta(L)) Y_t$$

$$H_t = [\Lambda_t \;\; -\Theta_1 \Lambda_{t-1} \;\; -\Theta_2 \Lambda_{t-2} \; \ldots \; \Theta_p \Lambda_{t-p} \; 0_{N \times q-p-1}]$$

with

$$\Theta(L) = (\Theta_1 + \Theta_2 + \cdots + \Theta_p)$$

Our state equation is:

$$F_t = \Phi F_{t-1} + \widetilde{\nu}_t \tag{14}$$

where $F_t = [f_t, f_{t-1}, \ldots, f_{t-q+1}]'$ is $q \times 1$, which is denoted as the state vector, $\widetilde{\nu}_t = [\nu_t \ 0 \ \ldots \ 0]'$ is $q \times 1$ and

$$\Phi = \begin{bmatrix} \varphi_1 & \varphi_2 & \cdots & \varphi_q \\ & \mathcal{I}_{q-1} & & 0_{q-1\times 1} \end{bmatrix}$$

which is $q \times q$. For all empirical results shown below we use $q > p$.

To calculate the common factor we use the algorithm suggested by Carter and Kohn (1994) and Frühwirth-Schnatter (1994). This procedure draws the vector $F = [F_1 \ F_2 \ \ldots \ F_T]$ from its joint distribution given by:

$$p(F|\Lambda, Y, \Xi) = p(F_T|\Lambda_T, y_T, \Xi) \prod_{t=1}^{T-1} p(F_t|F_{t+1}, \Lambda_t, \Xi, Y^t) \tag{15}$$

where $\Lambda = [\Lambda_1 \ \Lambda_2 \ \ldots \ \Lambda_T]$ and $Y^t = [Y_1 \ Y_2 \ \ldots \ Y_t]$. Because the error terms in equations (13) and (14) are Gaussian equation (15)can be rewritten as:

$$p(F|\Lambda, Y, \Xi) = N(F_{T|T}, P_{T|T}) \prod_{t=1}^{T-1} N(F_{t|t,F_{t+1}}, P_{t|t,F_{t+1}}) \tag{16}$$

with

$$F_{T|T} = E(F_T|\Lambda, \Xi, Y) \tag{17}$$
$$P_{T|T} = Cov(F_T|\Lambda, \Xi, Y) \tag{18}$$

and

$$F_{t|t,F_{t+1}} = E(F_t|F_{t+1}, \Lambda, \Xi, Y) \tag{19}$$
$$P_{t|t,F_{t+1}} = Cov(F_t|F_{t+1}, \Lambda, \Xi, Y) \tag{20}$$

We obtain $F_{T|T}$ and $P_{T|T}$ from the last step of the Kalman filter iteration and use them as the conditional mean and covariance matrix for the multivariate normal distribution $N(F_{T|T}, P_{T|T})$ to draw F_T. To illustrate the Kalman Filter we work with the state-space system equations (13) and (14). We begin with the prediction steps:

$$F_{t|t-1} = \Phi F_{t-1|t-1} \tag{21}$$
$$P_{t|t-1} = \Phi P_{t-1|t-1} \Phi + Q \tag{22}$$

where

$$Q = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & 0 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & 0 \end{bmatrix}$$

which is $q \times q$. To update these predictions we first have to derive the forecast error:

$$\kappa_t = Y_t^* - H_t F_{t|t-1} \tag{23}$$

its variance:

$$\Sigma = H_t P_{t|t-1} H_t' + \Omega_\chi \tag{24}$$

and the Kalman gain:

$$K_t = P_{t|t-1} H_t' \Sigma^{-1}. \tag{25}$$

Thus, the updating equations are:

$$F_{t|t} = F_{t|t-1} + K_t \kappa_t, \tag{26}$$

$$P_{t|t} = P_{t|t-1} + K_t H_t P_{t|t-1}, \tag{27}$$

To obtain draws for $F_1, F_2, \ldots, F_{T-1}$ we sample from $N(F_{t|t,F_{t+1}}, P_{t|t,F_{t+1}})$, using a backwards moving updating scheme, incorporating at time t information about F_t contained in period $t+1$. More precisely, we move backwards and generate F_t for $t = T-1, \ldots, p+1$ at each step while using information from the Kalman filter and F_{t+1} from the previous step. We do this until $p+1$ and calculate $f_1, f_2, \ldots, f_p$ in an one-step procedure.

The updating equations are:

$$F_{t|t,F_{t+1}} = F_{t|t} + P_{t|t}\Phi' P_{t+1|t}^{-1}(F_{t+1} - F_{t+1|t}) \tag{28}$$

and

$$P_{t|t,F_{t+1}} = P_{t|t} - P_{t|t}\Phi' P_{t+1|t}^{-1}\Phi P_{t|t} \tag{29}$$

5.3 Estimating the Time-Varying Factor Loadings

To estimate the time-varying factor loadings we condition on the parameters Ξ and the factor f_t.[12] Because equation (1) and equation (4) are N independent linear regressions, the factor loadings can be estimated equation by equation. Hence, we use the following state-space system and begin with the observation equation:

$$y_{i,t}^* = z_{i,t}\widetilde{\lambda}_{i,t} + \chi_{i,t} \tag{30}$$

[12] See also Del Negro and Otrok (2003).

where $y^*_{i,t} = (1-\theta(L)_i)y_{i,t}$, $z_{i,t} = [f_t \ \ -\theta_{i,1}f_{t-1} \ \ \ldots \theta_{i,p}f_{t-p}]$, which is $1 \times p+1$, $\widetilde{\lambda}_{i,t} = [\lambda_{i,t} \ \lambda_{i,t-1} \ \ \ldots \ \ \lambda_{i,t-p}]'$, which is $p+1 \times 1$ and with $\theta(L)_i = (\theta_{i,1}+\theta_{i,2}+\cdots+\theta_{i,p})$ for $i = 1, 2, \ldots, N$.

The state equation is:

$$\widetilde{\lambda}_{i,t} = A\widetilde{\lambda}_{i,t-1} \tag{31}$$

where

$$A = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ & \mathcal{I}_p & & 0_{p\times 1} \end{bmatrix}$$

which is $p+1 \times p+1$. After we have defined the state-space system, calculating the time-varying factor loadings is straightforward as we just have to apply the Carter and Kohn (1994) and Frühwirth-Schnatter (1994) algorithm described above.

Because $\widetilde{\lambda}_{i,t}$ follows a driftless random walk and hence is not a stationary process it is not possible to use the unconditional mean and variance as starting values for the Kalman filter anymore (Hamilton 1994, 378). Thus, we decided to use the estimates for the constant factor loadings as a proxy for the initial conditions[13].

[13]We applied this to simulated data and obtained very satisfying results.

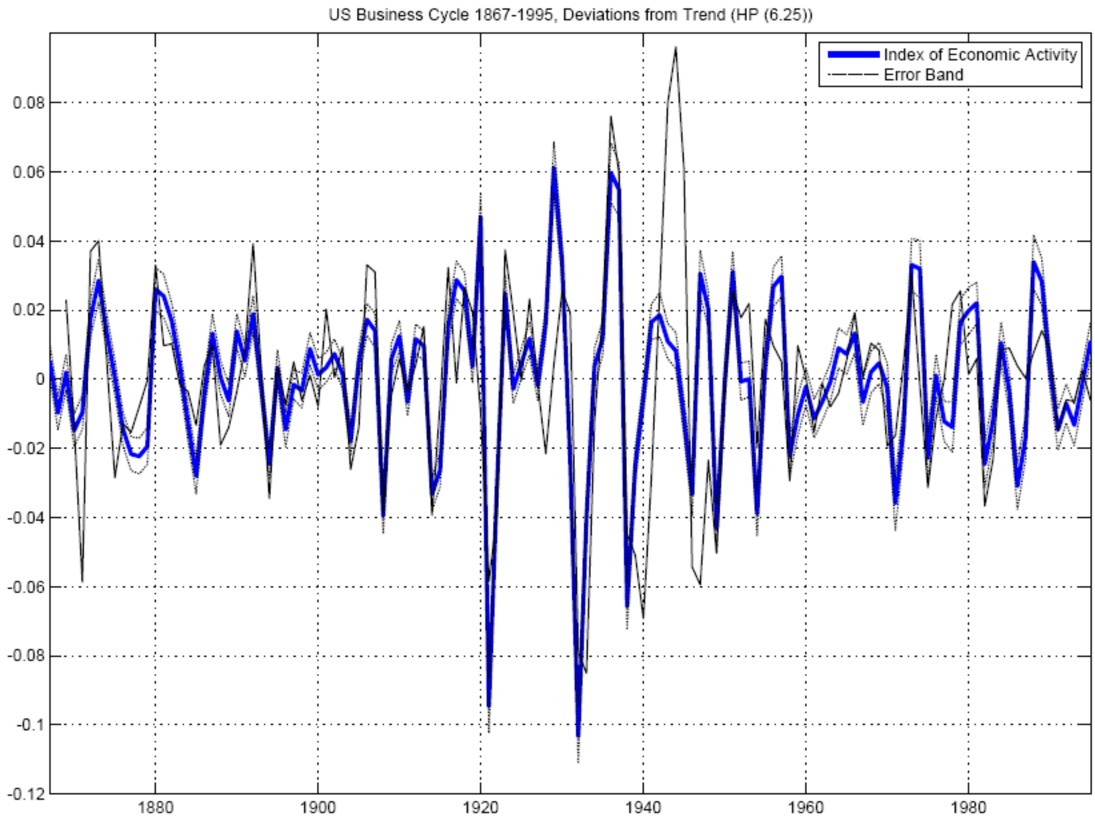

Figure 1: The US business cycle, 1867-1995. Factor vs GDP (1869-1929 Romer (1989), 1930-1995 NIPA). TVAR Factor from 53 series. GDP data are deviations from HP(6.25) trend, .

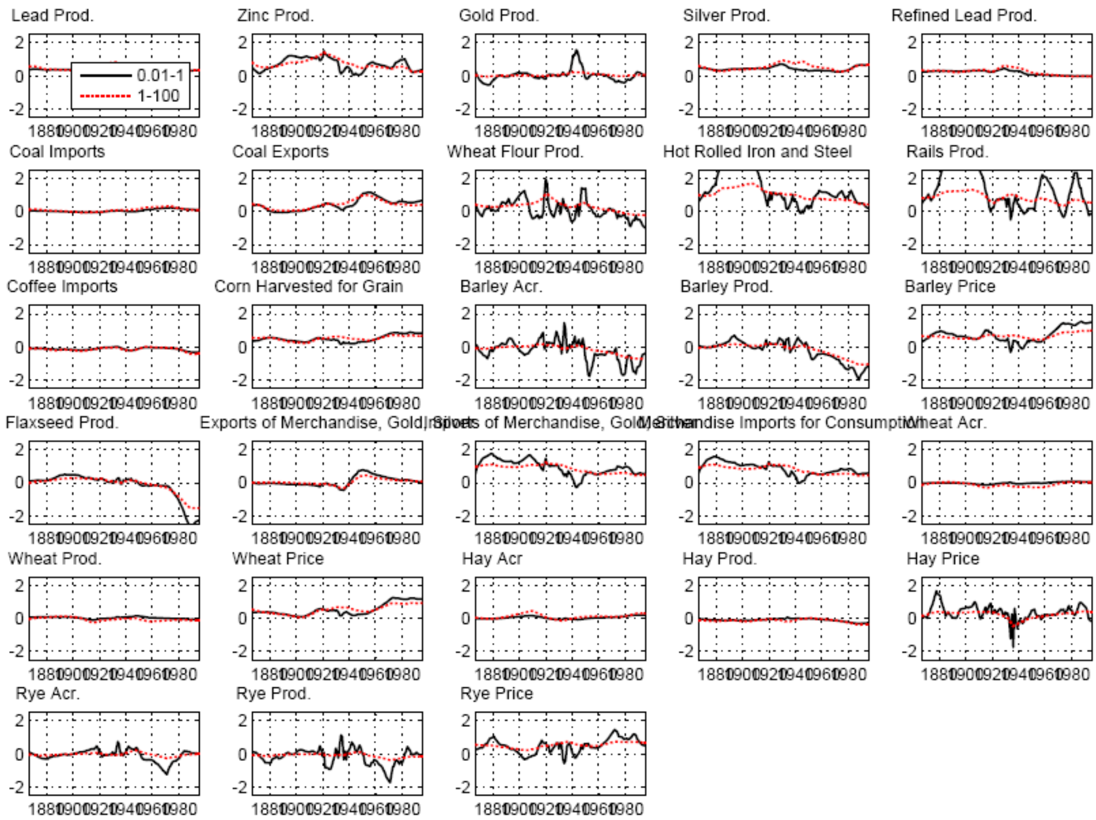

Figure 2: Factor Loadings, 1867-1995. Tight prior (red dotted line): $\delta_\epsilon = 1, \alpha_\epsilon = 100$. Loose prior (black continuous line): $\delta_\epsilon = 0.01, \alpha_\epsilon = 1$. Both priors imply the same mean of the IG distribution.

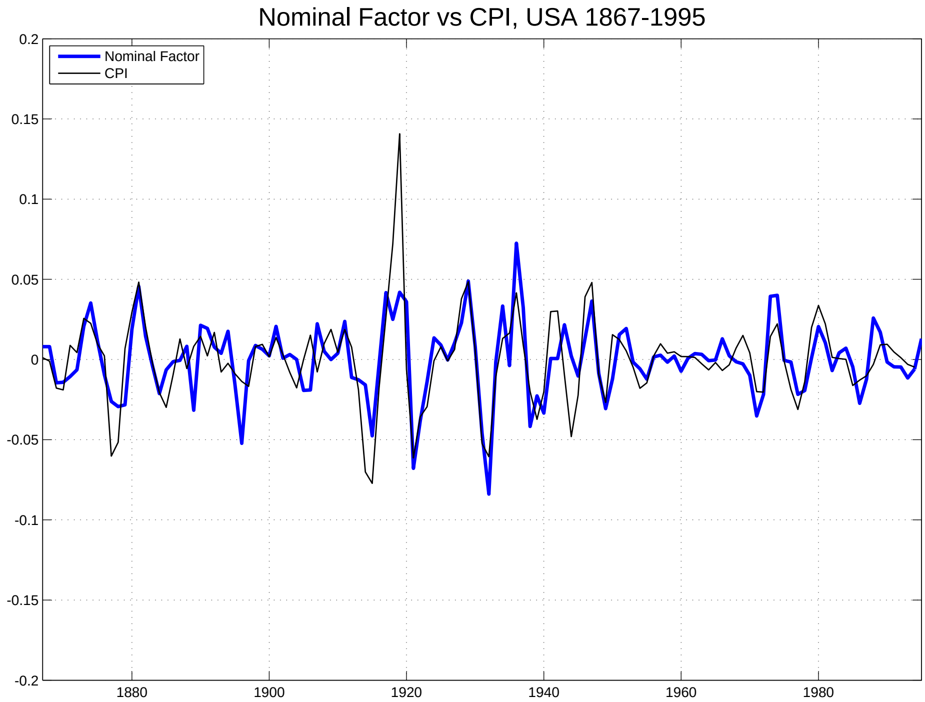

Figure 3: TVAR Factor from 17 nominal series vs US CPI. CPI data are deviations from HP(6.25) trend. Factor standardized to standard deviation of CPI (1946-1995). CPI annualized and shifted forwards by 1 year.

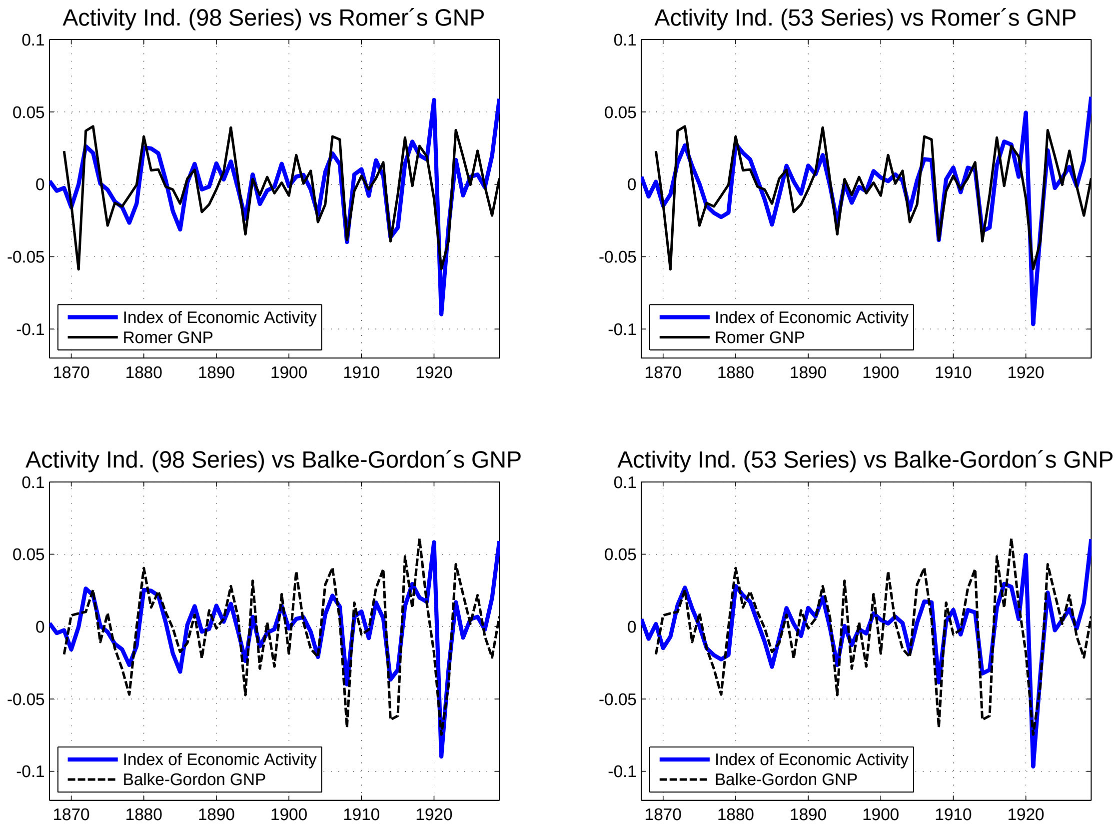

Figure 4: The US business cycle 1867-1929, Factor vs GNP estimates. TVAR Factors from 53 and 98 series, respectively. GDP data are deviations from HP(6.25) trend.

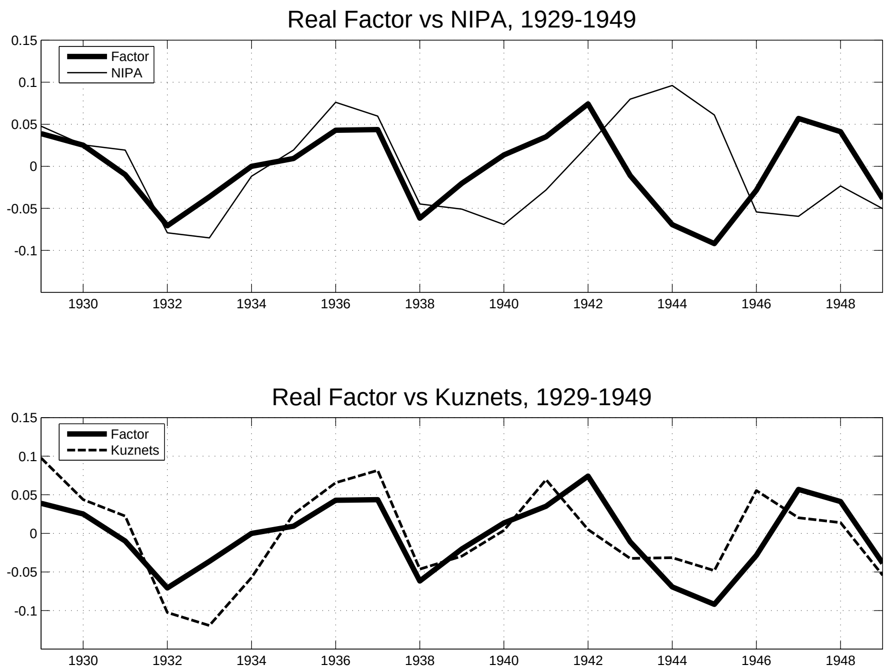

Figure 5: TVAR Factors from 36 real series vs. rivaling estimates of GNP during World War II. GDP data are deviations from HP(6.25) trend.

Table 1: Volatility Comparison, Post-World War II / Pre-World War I: Factor vs. GDP Estimates

Dev. from HP(6.25)-trend %	1867 -1913	1946 -95	Post-WW II /Pre-WW I
Romer GDP / NIPA	2.07	2.01	0.97
Balke/Gordon GDP / NIPA	2.47	2.01	0.81
FACTOR, ALL 53 SERIES			
Constant	2.00	2.01	1.01
Time Varying	1.51	2.01	1.33
FACTOR, NON-AGRICULTURAL REAL SERIES			
Constant	2.20	1.87	0.85
Time Varying	1.24	1.87	1.52
FACTOR, AGRICULTURAL REAL SERIES			
Constant	3.21	6.87	2.14
Time Varying	9.37	6.87	0.74
FACTOR, REAL NON-PHYSICAL OUTPUT SERIES			
Constant	1.46	2.01	1.38
Time Varying	1.84	2.01	1.09
FACTOR, NOMINAL SERIES			
Constant	1.32	1.62	1.23
Time Varying	1.93	1.62	0.84
FACTOR, NONAGR NOMINAL SERIES			
Constant	1.84	1.17	0.64
Time Varying	1.34	1.17	0.87
FACTOR, NONAGR NOMINAL SERIES			
Constant	7.17	8.30	1.16
Time Varying	7.53	8.30	1.10

Volatility of real series standardized to relevant NIPA subaggregates for 1946-95
Volatility of nominal series standardized to relevant sectoral GDP deflators for 1946-95

Table 2: Volatility Comparison Across World War I (1867-1929)

Std.Dev. from HP(6.25) Trend	1867 − 1913	1914 − 1929	1930 − 1939 (NIPA data)	1914 − 1929/ *Prewar*
GNP Estimates				
Romer	2.07	2.77	5.62	1.34
Balke-Gordon	2.47	4.10	5.62	1.66
1867-1995 dataset, normalized to NIPA 1946-1995				
FACTOR 53 SERIES				
Constant	2.00	5.25	6.92	2.63
Time Varying	1.51	3.54	5.02	2.34
1867-1929 dataset, normalized to Balke-Gordon 1867-1929				
FACTOR 53 SERIES				
Constant	1.96	4.95		2.51
Time Varying	1.97	4.95		2.51
FACTOR 98 SERIES				
Constant	2.38	4.34		1.82
Time Varying	2.18	4.70		2.16
1867-1939 dataset, normalized to NIPA 1930-39				
FACTOR 53 SERIES				
Constant	1.67	4.27	5.62	2.56
Time Varying	1.82	4.38	5.62	2.41
FACTOR 98 SERIES				
Constant	1.75	4.25	5.62	2.42
Time Varying	1.95	4.62	5.62	2.37

Table A-1: Data and Sources

	Series	Code	Units	98	53
1	Cargo moved on NY State canals	Df696	short tons	x	x
2	U.S. Tea Imports	m07040	mio pounds	x	
3	Prod. of Nonfarm Resid. Housekeeping Units	a02238	nr of units produced	x	
4	Nonfarm Nonresid. Building Activity	a02240	mio current dollars	x	
5	Total Nonfarm Building Activity	a02241	mio current dollars	x	
6	Live Hog Receipts	m01038	thousands of head	x	
7	Rail Consumption	a02084	1000 long tons	x	
8	Merchant Vessels	a02244	gross tons	x	
9	Building Permits, Chicago	a02047	mio current dollars	x	
10	Merchant Marine	a02135	1000 gross tons	x	
11	Yachts Built	a02102	gross tons	x	
12	Nonfarm Resid. Building Activity	a02239	mio current dollars	x	
13	Raw Silk Imports	m7037a-c	thousands of tons	x	
14	Coffee Imports	m07038	mio of pounds	x	
15	Tin Imports	m07042	long tons	x	
16	Raw Cotton Exports	m07043a	mio of pounds	x	
17	Miles of Railroad Built	a02082a	miles	x	
18	Nr. of Concerns in Business	a10030	thousands	x	
19	Index of US Business Activity	m12003	percent of trend	x	
20	Bank Clearings	m12015	Daily Average	x	
21	Wholesale Price Cotton, raw	m04006a	cents per pound	x	x
22	Whs. Price of Wheat, Chicago, 6 Markets	m04001a	cents per bushel	x	
23	Wholesale Price of Corn Chicago	m04005	dollars per bushels	x	
24	Wholesale Price of Cattle Chicago	m04007	dollars per hundred pounds	x	
25	Wholesale Price of Hogs Chicago	m04008	1000 tons	x	
26	Copper Prices	Cc253-258	Dollars per pound	x	
27	Brick Prices	Cc264-266	dollars per thousand	x	
28	Prices of Anthr. Foundry Pig Iron	m04011a	dollars per ton of 2240 lbs.	x	
29	Whs. Price of Copper	m04015a	cents per pound	x	
30	Total Exports	m07023	mio of dollars	x	
31	Total Imports	m07028	mio of dollars	x	
32	Earnings Yield NYSE Common Stocks	a13049	%	x	
33	Index of Whs. Prices	Cc125		x	
34	Index General Price Level	m04051	cents per pound	x	
35	Call Money Rates Mixed Coll.	m13001	%	x	
36	Am. Railroad Bond Yields	m13019	%	x	
37	National Bank Notes Outst.	m14124a	mio of dollars	x	
38	Comm. Paper Rates NY City	m13002	%	x	
39	Oats production	Da667-678	Thousand metric tons	x	x
40	Cotton production	Da755-765	Thousand short tons	x	x
41	Raw steel production	Dd399	Thousand short tons	x	
42	Patents granted	Cg38	Number	x	x
43	Stock Prices	Cj797*	1802=10	x	x
44	US Notes	Cj60	thousand dollars	x	x
45	Business Failures	Ch411	Number	x	x
46	Coal Fuel Mineral Production	Db25-33	Thousand short tons	x	x
47	Vessels entered US ports	Df594	thousand net tons	x	x
48	Wool Prices	Cc226-230	Dollars per pound	x	x
49	Coal Prices	Cc235-242	Dollars per ton of 2240 lbs.	x	x
50	Irish potatoes Acreage	Da 768	Thousand acres	x	x
51	Irish potatoes Production	Da 769	Thousand tons	x	x
52	Irish potatoes price	Da 770	dollars per hundred weight	x	x
53	Cattle Nr	Da 968	Number	x	x
54	Cattle Price	Da 969	Value per head	x	x
55	Hogs Nr	Da 970	Number	x	x
56	Hogs Price	Da 971	Value per head	x	x
57	Cows and heifers	Da1020	Number	x	x
58	Cows and heifers	Da 1021	Value per head	x	x
59	Butter Price	Da 1036	Cents per pound	x	
60	Petroleum Price	Db 56	Average value at well	x	x
61	Bit. Coal Production	Db 60	Thousand short tons	x	x
62	Bit. Coal Imports for Consumption	Db 64	Thousand short tons	x	
63	Bit Coal Exports	Db 65	Thousand short tons	x	
64	Pig iron shipments	Db 74	Thousand short tons	x	x
65	Production from mines	Db 75	metric tons	x	x
66	Lead production	Db 80	metric tons	x	x

Overview cont'd

	Series	Code	Units	98	53
67	Zinc production	Db 84	metric tons	x	x
68	Gold production	Db 94	kg	x	x
69	Silver production	Db 95	metric tons	x	x
70	Refined lead imports	Db 146	metric tons	x	x
71	Coal Exports	Db 191	Thousand short tons	x	x
72	Wheat flour	Dd 368	Thousand short tons	x	x
73	Hot rolled iron and steel	Dd 405	Thousand short tons	x	x
74	Rails	Dd 407	Thousand short tons	x	x
75	Corn/Harvested for grain	Da 697	Acreage Harvested	x	x
76	Coffee, imported	Dd843	Million pounds	x	x
77	Telegraph Operating Revenues	Dg 19 /Dg 18	Million dollars	x	
78	Barley acreage harvested	Da701	Thousand acres	x	x
79	Barley Production	Da702	Thousand bushels	x	x
80	Flaxseed	Da705	Dollars per hundredweight	x	x
81	Exports of merchandise, gold, and silver	Ee362	Dollars	x	x
82	Imports of merchandise, gold, and silver	Ee363	Dollars	x	x
83	Exports and Imports	Ee1	Million dollars	x	x
84	Merchandise Imports and Duties	Ee 425	Dollars	x	x
85	Cotton, unman. exports	Ee571	Million dollars	x	
86	Tea Imports	Ee594	Cents per pound	x	
87	Sugar Imports	Ee596	Dollars per barrel	x	
88	All wheat acreage	Da717	thousand acres	x	x
89	All wheat production	Da718	million bushels	x	x
90	All wheat price	Da719	dollars per bushels	x	x
91	Hay acreage	Da733	Thousand acres	x	x
92	Hay production	Da734	Thousand bushels	x	x
93	Hay price	Da735	Dollars per short ton	x	x
94	Rye acreage	Da740	Thousand acres	x	x
95	Rye production	Da741	Thousand bushels	x	x
96	Rye price	Da742	dollars per bushel	x	x
97	Net Savings of Life Ins. Policy Holders	a10036a	Million dollars	x	
98	Population	Aa7	Thousand	x	x

*from 1871-1896: Cowles Comm. (m11025a). 1867-1870: Railroad stocks (m11005).

Source: A-, C-, D-, E-codes: Historical Statistics of the United States (Carter et al., 2006)
a-, m-codes: NBER macro history database (www.nber.org/databases/macrohistory/contents/)

Table A-2: Volatility by Decade, 53 Series, 1867-1995, Sectoral Subsets
Constant and Time-Varying Factor Loadings

Dev. from HP-trend%	1867 -1913	1914 -29	1930 -39	1946 -95	1950 -59	1960 -69	1970 -79	1980 -95	Postwar /Prewar
Romer GNP	2.07	2.78	6.00	2.01	2.98	0.98	2.06	1.34	0.97
Balke/Gordon GNP	2.47	4.10	6.00	2.01	2.98	0.98	2.06	1.34	0.81
ALL 53 SERIES									
Constant	2.00	5.25	6.92	2.01	2.49	1.12	1.86	1.74	1.01
Time Varying	1.51	3.54	5.02	2.01	2.22	0.90	2.25	1.90	1.33
NON-AGRICULTURAL SERIES									
Constant	2.00	4.70	6.40	1.87	2.54	1.03	1.40	1.54	0.87
Time Varying	1.40	2.47	5.13	1.87	2.83	0.83	1.66	1.03	1.25
AGRICULTURAL SERIES									
Constant	5.71	9.13	15.96	6.87	4.61	2.80	10.19	6.87	4.10
Time Varying	5.71	10.36	19.89	6.87	7.31	3.08	8.89	6.08	4.14
REAL SERIES									
Constant	1.70	3.55	3.98	2.01	2.82	0.88	1.44	1.26	1.18
Time Varying	1.21	2.27	3.82	2.01	2.19	1.46	1.64	1.58	1.66
NONAGR REAL SERIES									
Constant	2.20	4.68	6.18	1.87	2.50	0.99	1.67	1.67	0.79
Time Varying	1.24	2.06	3.54	1.87	2.20	1.10	1.27	1.55	1.41
AGRICULTURAL REAL SERIES									
Constant	3.21	7.31	16.20	6.87	7.45	6.15	8.75	5.67	7.31
Time Varying	9.37	10.46	16.13	6.87	7.96	5.84	8.10	5.43	2.53
NOMINAL SERIES									
Constant	1.32	2.93	3.84	1.62	0.98	0.70	2.53	1.57	1.23
Time Varying	1.93	3.28	4.39	1.62	1.15	0.74	2.44	1.39	0.84
NONAGR NOMINAL SERIES									
Constant	1.84	3.00	3.57	1.17	1.65	0.77	1.41	0.89	0.46
Time Varying	1.34	1.45	1.88	1.17	0.95	0.84	1.67	0.94	0.64
AGRICULTURAL NOMINAL SERIES									
Constant	7.17	12.55	18.44	8.30	4.51	3.64	12.81	7.99	5.94
Time Varying	7.53	12.60	16.09	8.30	4.76	3.95	12.86	7.69	5.64

Factors estimated for 1867-1995. Std.dev. of aggregate and real series standardized to NIPA for 1946-1995. Std.dev. of nominal series standardized to CPI 1946-1995.