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**Article (Published version)
(Refereed)**

Original citation:

Ritschl, Albrecht, Sarferaz, Samad and Uebele, Martin (2016) *The U.S. business cycle, 1867–2006: a dynamic factor approach*. [The Review of Economics and Statistics](#), 98 (1). pp. 159-172.
ISSN 0034-6535
DOI: [10.1162/REST_a_00530](https://doi.org/10.1162/REST_a_00530)

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This version available at: <http://eprints.lse.ac.uk/67420/>
Available in LSE Research Online: August 2016

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THE U.S. BUSINESS CYCLE, 1867–2006: A DYNAMIC FACTOR APPROACH

Albrecht Ritschl, Samad Sarferaz, and Martin Uebele*

Abstract—We estimate a Stock/Watson index of economic activity to assess U.S. business cycle volatility since 1867. We replicate the Great Moderation of the 1980s and 1990s and find exceptionally low volatility also in the Golden Age of the 1960s. Postwar moderation relative to pre-1914 occurs under constant but not time-varying factor loadings, suggesting structural change toward more volatile sectors. For comparable series, the U.S. postwar business cycle was as volatile overall as under the Classical Gold Standard, but much less so during the Great Moderation and the Golden Age.

I. Introduction

THE Great Recession after 2007 is often seen as a major departure from the muted business cycle volatility observed since the end of the 1979 recession. Dubbed the Great Moderation, this pattern has been studied extensively in recent research (see Kim & Nelson, 1999a; McConnell & Perez-Quiros, 2000; Stock & Watson, 2002; Jaimovich & Siu, 2008; Gambetti & Gali, 2009; Giannone, Lenza, & Reichlin, 2008; Justiniano & Primiceri, 2008; Canova, 2009). The then recent adoption of inflation targeting was a popular candidate explanation (“good policy”); an exogenous reduction in shocks hitting the U.S. economy (“good luck”) was one alternative, as were sectoral composition effects and the possible effects of just-in-time delivery on the volatility of output. A much wider historical interpretation also existed. In earlier research, DeLong and Summers (1986) had argued for business cycle moderation in the long run, observing that postwar U.S. business cycles had become less volatile compared to the period before World War I, and certainly so than in the interwar period. They already made the connection to new macroeconomic doctrines, the IS-LM paradigm informing monetary and fiscal policy after World War II as opposed to the gold standard prevailing before 1914.

This paper is about studying moderation in the U.S. economy prior to 2006 in a long-term perspective, going all the way back to 1867. We use panels of different sizes to identify patterns of volatility along the time axis and across sectors. Disaggregate postwar evidence studied by Stock and Watson (2002) suggested time-varying volatility of shocks in both

univariate analysis and a VAR, while time variation in the coefficients played less of a role. Studying nominal data, Cogley and Sargent (2005) found a role for increased persistence of inflation rates, while Primiceri (2005) argued that such changes may have had little effect on real activity.

We follow much of the recent literature in favoring disaggregate data over prefabricated GDP aggregates. A strong additional motivation in our long-run study is the increasing uncertainty over the quality of these aggregates for more distant historical periods. Because the official NIPA series of national accounts starts only in 1929, the database available for constructing national accounts becomes progressively narrower going back in time. Estimates by Balke and Gordon (1986, 1989) and Romer (1986, 1988) differed on the amount of volatility in pre-1914 business cycles, with different implications for postwar moderation. In addition, modern research has characterized the pre-1914 gold standard as a system of surprisingly sophisticated commitment mechanisms for fiscal policy that proved robust to financial crises and high public debt levels (see Bordo & Kydland, 1995). In the light of these findings, we set out to provide new measures of U.S. business cycle activity since the end of the Civil War and identify periods of low volatility and their possible connections to monetary regimes.

To obtain intertemporally consistent measures of economic activity and its volatility, we draw on the literature on diffusion indices (using a term of Stock & Watson, 1998) of economic activity, 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 replicates the NBER’s business cycle turning points. We adopt a variant of this approach for our work and use the resulting activity index as our yardstick.

Factor-based indices of economic activity have become popular because they reliably aggregate information from highly diverse individual and disaggregate series 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. Usually, however, they do not match national accounting categories very well, and the Census information needed for proper aggregation is incomplete or even missing. As a consequence, national accounts for historical periods (or, for that matter, in emerging economies) have to be constructed from less-than-representative proxies and may fail to efficiently exploit the information that is available for the respective economy from that period. Activity measures obtained through dynamic factor analysis replace these index calculations with a statistical aggregation procedure. Series that would be of limited use in constructing national accounts can still be informative about business cycle dynamics through their contribution to the common component. To our knowledge, this approach

Received for publication March 12, 2012. Revision accepted for publication January 5, 2015. Editor: Mark W. Watson.

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Thanks are due to Pooyan Amir Ahmadi, Barry Eichengreen, Ayhan Kose, Peter Lindert, Bartosz Maćkowiak, Marco del Negro, Wolfgang Reichmuth, Christina Romer, Harald Uhlig, and participants in several conferences and seminars. Financial support from Deutsche Forschungsgemeinschaft through SFB 649 “Economic Risk” at Humboldt University of Berlin is gratefully acknowledged. Support also came from the Marie Curie Research Training Network “Unifying the European Experience.” Dun&Bradstreet Corp. generously provided data. A discussion paper version of this paper was distributed under the title “The U.S. Business Cycle, 1867–1995: A Dynamic Factor Approach.”

A supplemental appendix is available online at http://www.mitpressjournals.org/doi/suppl/10.1162/REST_a_00530.

was first employed for the long term by Gerlach and Gerlach-Kristen (2005) for Switzerland between the 1880s and the Great Depression of the 1930s. Sarferaz and Uebele (2009) employ dynamic factor analysis to obtain an index of economic activity for nineteenth-century Germany, comparing it to different chronologies based on reconstructed national accounts.

To study the evolution of U.S. business cycle volatility over time, we carry out two main exercises. The first covers the full sample from 1867 to 2006. We obtain aggregate and sectoral factors, as well as real and nominal ones. The second group of exercises examines the change in volatility across the world wars. For the long-term comparison, we include 52 time series available on an unchanged methodological basis. For the second exercise, we can employ up to 98 such series. Data are taken from the *Historical Statistics of the United States* (Carter et al., 2006), as well as the NBER's Macrohistory Database, which itself dates back to the business cycle project of Burns and Mitchell (1946).

Factor models offer two ways to deal with time variation in the indices computed. The Stock/Watson methodology relies on drawing more than one common component, aiming to map time variation into second and third principal components. An alternative is to allow for time variation in the factor loadings of a one-factor model explicitly, specifying a law of motion and controlling its evolution through prior assumptions on the variance of the underlying stochastic process. We follow the second path, adopting the Bayesian dynamic factor model of Del Negro and Otrok (2003, 2008). In the context of our model, this is akin to modeling structural change, which in a long-term analysis like ours must play a role. One of our principal findings is that we can reproduce the conventional wisdom on postwar moderation relative to pre-1914 when shutting down this channel, that is, when assuming constant factor loadings. This result echoes Romer's (1986) finding that lack of adjustment for structural change may induce spurious volatility in historical output series.

While we can reproduce the traditional evidence on postwar moderation under constant factor loadings, this is less clear once time variation is allowed. Based on time-varying factor loadings, the second principal finding of our paper is that, indeed, the postwar business cycle may have been more volatile overall than before 1914.

Not all long-run structural change can be captured by changing index weights. The emergence of new industries and sectors brings in all the well-known problems of intertemporal comparison. Our modeling approach makes these issues explicit, purposefully limiting our research to those groups of economic phenomena that admit like-for-like comparison. Even within this narrower class, we achieve clear results. A third principal finding of this paper is that we replicate the standard evidence on the Great Moderation after the 1980s (see, e.g., Cogley & Sargent, 2005; Primiceri, 2005; Gambetti & Gali, 2009; Giannone et al., 2008). Our results suggest that aggregate volatility during

the Great Moderation may not have been lower than during the Classical Gold Standard. However, for some subsets of the data we find volatility during the Great Moderation to have been around 30% to 40% lower than before 1913, and probably 50% lower in services. The major exception is physical output in the nonfarm economy, although even here, there is a sharp drop in volatility relative to the 1970s. All of these results imply that the Great Moderation was not merely due to new sectors that our panel cannot capture, although this effect certainly played an added role. We do not find very strong postwar moderation in the nominal series overall when compared to pre-1914. However, nominal series pertaining to the nonfarm economy were one-third less volatile during the postwar period and 50% less volatile during the Great Moderation than under the Classical Gold Standard.

Stochastic aggregate volatility should be visible in all sectors of the U.S. economy, both traditional subsectors and more modern. The third principal finding of this paper is that stochastic volatility of the U.S. economy since the Civil War followed a hump-shaped pattern that peaked in the Great Depression but built up significantly earlier and took a long time to dissipate after that. This secular hump-shaped pattern is very much the same across all subsectors of our data, confirming that the shocks are indeed aggregate.

Changing business cycle volatility was accompanied by changes in nominal volatility. Nonagricultural nominal series were noticeably more moderate throughout the postwar period, while agricultural prices may have been more volatile than during the gold standard. The relevant principal finding, though, is that the pattern of shocks to our nominal subset of data is essentially the same as for the data set as a whole.

The remainder of the paper is structured as follows. Section II briefly sketches the Bayesian factor model and discusses the specifications we adopt. Section III presents the long-run evidence. Sections IV and V discuss changes in volatility across the two world wars. Section VI concludes. Technical derivations, data sources, and more detailed results appear in the online appendixes.

II. A Bayesian Dynamic Factor Model

A. Setup

Dynamic factor models in the tradition of Sargent and Sims (1977), Geweke (1977), and Stock and Watson (1989) assume that a panel data set can be characterized by one or more latent common components that capture the comovements of the cross section, as well as a variable-specific idiosyncratic component. These models imply that economic activity is driven by a small number of latent driving forces, which are captured by the dynamic factors. A Bayesian approach to dynamic factor analysis is provided by Otrok and Whiteman (1998) and Kim and Nelson (1999b), among others. Del Negro and Otrok (2008) generalize the estimation procedure to dynamic factor models with time-varying

parameters and stochastic volatility. We closely follow their methodology.

We describe the data panel Y_t , spanning a cross section of N series and an observation period of length T by a one-factor model with time-varying factor loadings. The observation equation then is

$$Y_t = \Lambda_t f_t + U_t, \quad (1)$$

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 data set and is our primary object of interest.¹ We assume that the factor evolves according to an AR(q) process:

$$f_t = \varphi_1 f_{t-1} + \dots + \varphi_q f_{t-q} + v_t, \quad (2)$$

with $v_t = e^{h_t} \xi_t$ and $\xi_t \sim \mathcal{N}(0, 1)$. The log volatility h_t follows a random walk without drift:

$$h_t = h_{t-1} + \eta_t, \quad (3)$$

where $\eta_t \sim \mathcal{N}(0, \sigma_\eta^2)$.

The idiosyncratic components U_t are assumed to follow an AR(p) process:

$$U_t = \Theta_1 U_{t-1} + \dots + \Theta_p U_{t-p} + \chi_t, \quad (4)$$

where $\Theta_1, \dots, \Theta_p$ are $N \times N$ diagonal matrices and $\chi_t \sim \mathcal{N}(0_{N \times 1}, \Omega_\chi)$ with

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

The factor loadings or coefficients on the factor in equation (1), Λ_t , are assumed to either be constant or (in the time-varying model) follow a driftless random walk, as in del Negro and Otrok (2003, 2008):²

$$\Lambda_t = \mathcal{I}_N \Lambda_{t-1} + \epsilon_t, \quad (5)$$

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

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

¹ Generalization to several factors is straightforward.

² An alternative approach to capturing time variation is to specify multi-factor models with constant factor loadings, where higher-order factors are interpreted as correction factors that pick up the time variation.

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

The dynamic factor in this model is identified up to a scaling constant. Following Del Negro and Otrok (2008), we deal with scale indeterminacy by fixing the initial value of the log volatility to $h_0 = 0$.³

B. Priors

Before proceeding to the estimation of the system, we specify prior assumptions. For the most part, these priors are chosen as convenient initial conditions for burn-in of the Markov chains, without affecting their steady states. Other priors are informative and have a substantive interpretation in terms of our research question, the time variation taken up by the factor loadings rather than the factor itself. To tackle this, we obtain results for different degrees of tightness of these priors, varying from diffuse to rather tight. We adopt priors for four groups of parameters of the above system. These are, in turn, the parameters in the observation equation (1), the parameters in the factor equation (2), the parameters in the stochastic volatility equation (3), the parameters in equation (4) governing the law of motion of the idiosyncratic component, and the parameters in the law of motion of the factor loadings, equation (5).

For the AR parameters $\varphi_1, \varphi_2, \dots, \varphi_q$ 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

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

Analogously, for the AR parameters $\Theta_1, \Theta_2, \dots, \Theta_p$ 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

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

We choose $\tau_1 = 0.2$ and $\tau_2 = 1$. Both priors are shrinkage priors that punish more distant lags on the autoregressive

³ See Del Negro and Otrok (2008) for a more thorough discussion.

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 0 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:

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

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

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

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

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

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

Specification of priors relating to the factor loadings is a key element of our research strategy. We adopt constant factor loadings as one benchmark case and a diffuse prior on σ_{ϵ}^2 as the other. These benchmarks can be considered as polar opposites. Under the first, no structural change is allowed and all time variation is assigned to the factor f_t . Under the second, maximum structural change is allowed, and it is (somewhat loosely speaking) left to the maximum likelihood estimator to allocate time variation between the factor, stochastic volatilities, and the factor loadings. For the somewhat informative prior ($\alpha_{\epsilon} = 101$ and $\delta_{\epsilon} = 0.1$) reported there (and throughout the paper), the factor loadings change gradually at frequencies well below business cycle frequencies (see figures 2 and 3). We regard this as a plausible description. However, by using a more diffuse prior, for example, ($\alpha_{\epsilon} = 11$ and $\delta_{\epsilon} = 0.01$), it becomes clear that nothing depends on this preference qualitatively.⁴

For the variances of the innovations in η_t , we specified the following prior:

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

We choose $\alpha_{\eta} = 101$ and $\delta_{\eta} = 0.1$.⁵

C. Estimation

We estimate the model by Gibbs sampling. In our case, the estimation procedure is subdivided into four blocks. First,

the parameters of the model $\varphi_s, \theta_r, \sigma_g$ for $s = 1, \dots, q$, $r = 1, \dots, p$, and $g = \chi, \epsilon, \eta$ are calculated. Second, conditional on the estimated values of the first block, the factor f_t is computed. Third, conditional on the results of the first two blocks, we estimate the factor loadings. Finally, conditional on the results of the previous blocks, we estimate the stochastic volatility. After the estimation of the fourth 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 & Geman, 1984).

We obtained estimates for lag lengths $p = 1, q = 8$, taking 100,000 draws and discarding the first 80,000 as burn-in. Specifications with constant and time-varying factor loadings are reported alongside each other. Convergence of the Gibbs sampler was checked using numerical diagnostics and visual inspections. All convergence diagnostics conducted were satisfactory.⁷ All series were detrended using the Hodrick-Prescott (6.25) filter suggested by Ravn and Uhlig (2002) for business cycle frequencies, and were subsequently standardized.⁸

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

In this section we present results on the American business cycle between 1867 and 2006 in its entirety. We are interested in both volatility itself and its proximate sources. Volatility in our factor model originates from two main sources, the loadings and lag structure of the factor model itself, as well as stochastic volatility operating on the model exogenously. We consider them in turn.

Figure 1 is our representation of the American business cycle between 1867 and 2006. It shows a one-factor model of aggregate economic activity under time-varying factor loadings from 52 time series available on a consistent basis for the whole period. The official NIPA series of GDP starting in 1929 and a GDP estimate of Romer (1989) for 1869 to 1929 are shown for comparison. The factor is calibrated to the standard deviation of the NIPA series from its HP (6.25) trend for 1946 to 2006.

As figure 1 bears out, 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 nineteenth century (see Davis, Hanes, & Rhode, 2007, for details on the chronology). Differences with the GDP data emerge around the world wars. The recessions of 1920–1921 and 1931 come out more strongly in the factor than in the GDP estimates. Also, our factor shows a much milder increase in activity during World War II than the NIPA series

⁴ Results can be made available on request.

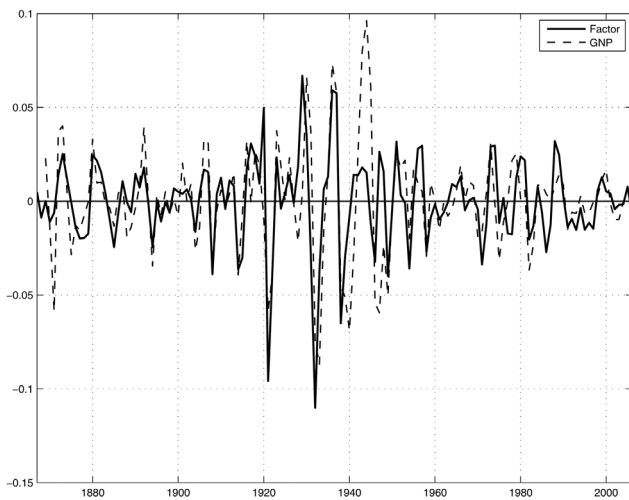
⁵ We also experimented with less informative priors, for example, ($\alpha_{\eta} = 11$ and $\delta_{\eta} = 0.01$), however without qualitative changes to the principal findings.

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

⁷ See online appendix C for a more detailed discussion.

⁸ We also experimented with $\lambda = 100$, as well as with Baxter/King and first-difference filters, and found the qualitative results to be robust.

FIGURE 1.—THE U.S. BUSINESS CYCLE, 1867–2006



Factor versus GDP (1869–1929, Romer, 1989; 1930–2006 NIPA). TVAR factor from 52 series. GDP data are deviations from HP(6.25) trend. Time-varying factor loadings and stochastic volatilities.

of GDP. We discuss these results in more detail in sections IV and V. We also see that the factor is substantially more volatile during the interwar period than before or after the wars. However, it is not obviously less volatile after 1945 than before 1914. This invites a closer look.

A. The Role of Factor Loadings

The factor shown in figure 1 is based on time varying factor loadings under our preferred, mildly informative prior. Figures 2 and 3 show how these 52 factor loadings evolve over our observation period. As can be seen, the factor loadings change smoothly over time while suppressing volatility at business cycle frequencies. This result is robust even under a very diffuse prior. The absence of cyclical components from the loadings implies that volatility at the relevant business cycle frequencies is indeed captured by the factors themselves.⁹

Factor estimates as in figure 1, representing aggregate or sectoral activity, are our yardstick for intertemporal comparisons of U.S. business cycle volatility. Table 1 compares volatility of several such factors 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.¹⁰ The GDP estimates of Romer (1989) and Balke and Gordon (1986, 1989), designed in different ways to backcast the NIPA data on GDP backward from 1929, provide the relevant comparison for the period prior to World War I.

In table 1, the volatility of all data is calibrated to NIPA for the postwar period. Panel A provides results for the volatility of GDP. For the pre-1914 period, Balke and Gordon's GDP estimate is more volatile than post–World War

II GDP, indicating postwar moderation in the U.S. business cycle. This replicates the traditional postwar moderation result that caught the attention of DeLong and Summers (1986) and others. Romer's (1989) estimate of pre-1914 GDP is less volatile, suggesting very little postwar moderation relative to the prewar business cycle. In both estimates, however, volatility during the 1960s and again during the Great Moderation of 1980 to 2006 seems markedly lower than pre-1914.

Table 1 also reports results from our factor model, always for both time-varying and constant factor loadings. Results obtained for the aggregate factor from all 52 series, obtained under time-varying factor loadings and stochastic volatility as in figure 1, show no postwar moderation overall. Indeed the postwar business cycle comes out as slightly more volatile than before 1914. We do obtain the Great Moderation after the 1980s, as well as the Golden Age of the 1960s with its characteristic lull in business cycles. This result carries over to most subsets of the data, with the interesting exception of the nonagricultural real series (see table 2), which would suggest that output in the nonagricultural economy was still highly volatile in the 1950s and only subsequently experienced moderation.

By contrast, under constant factor loadings, there is some (although insignificant) postwar moderation relative to pre-1914 in the aggregate factor.¹¹ The Great Moderation of the 1980s and the Golden Age come out more strongly than under time-varying factor loadings. This is particularly true for the nonagricultural economy, in contrast to the results obtained under time-varying factor loadings (see table 1). Overall, the model under constant factor loadings delivers the traditional result. Given that constant factor loadings shut down structural change, this seems surprising. An estimation procedure tilted toward ignoring composition effects should yield higher, not lower, volatility. After all, this was Romer's (1986) point about spurious volatility in reconstructed historical estimates of GDP.

This paradox is resolved when comparing our results for constant factor loadings with those obtained under time-varying factor loadings. For the pre-1914 gold standard, the volatility of many of the factor estimates is markedly lower than when factor loadings are allowed to vary, and it is equal across both methods for 1946 to 2006 by construction (see tables 1 and 2). This would suggest that Romer was right: shutting down structural change in GDP estimates of Balke and Gordon leads to an increase in volatility. Calculating these into the volatility data for the postwar period mechanically but spuriously delivers postwar stabilization.

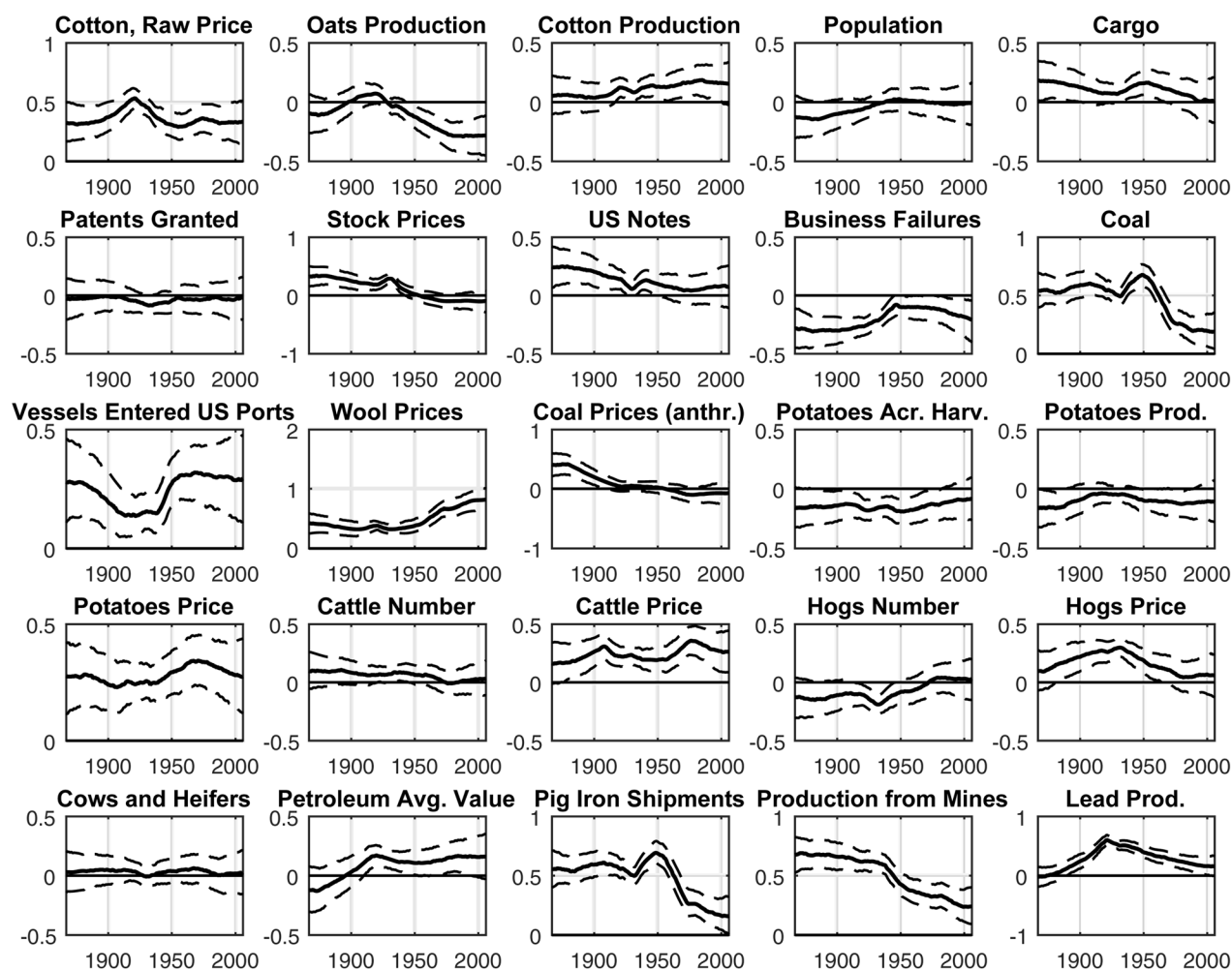
This result also carries over to aggregate stochastic volatility (see figure 5 (bottom)). With time-varying factor loadings, stochastic volatility increases steeply from as early as 1900 to the recession of 1921, and further until

⁹ Results are obtainable from the authors on request.

¹⁰ Table 3 lists additional results for several sectoral subsets of time series.

¹¹ These estimates were obtained allowing for stochastic volatility. Results for constant factor loadings with constant variance are in the working paper version of this paper or can be obtained on request.

FIGURE 2.—TIME-VARYING FACTOR LOADINGS, 1867–2006



Part 1. Solid lines represent the posterior mean, and dotted lines are the 16th and 84th percentiles.

1933. Constant factor loadings, however, deliver a strong fall in stochastic volatility before 1900 and a subsequent increase, making the average level of volatility before 1914 appear much higher relative to the rest of the observation period. As a consequence, postwar stabilization is much more pronounced when factor loadings are kept fixed.

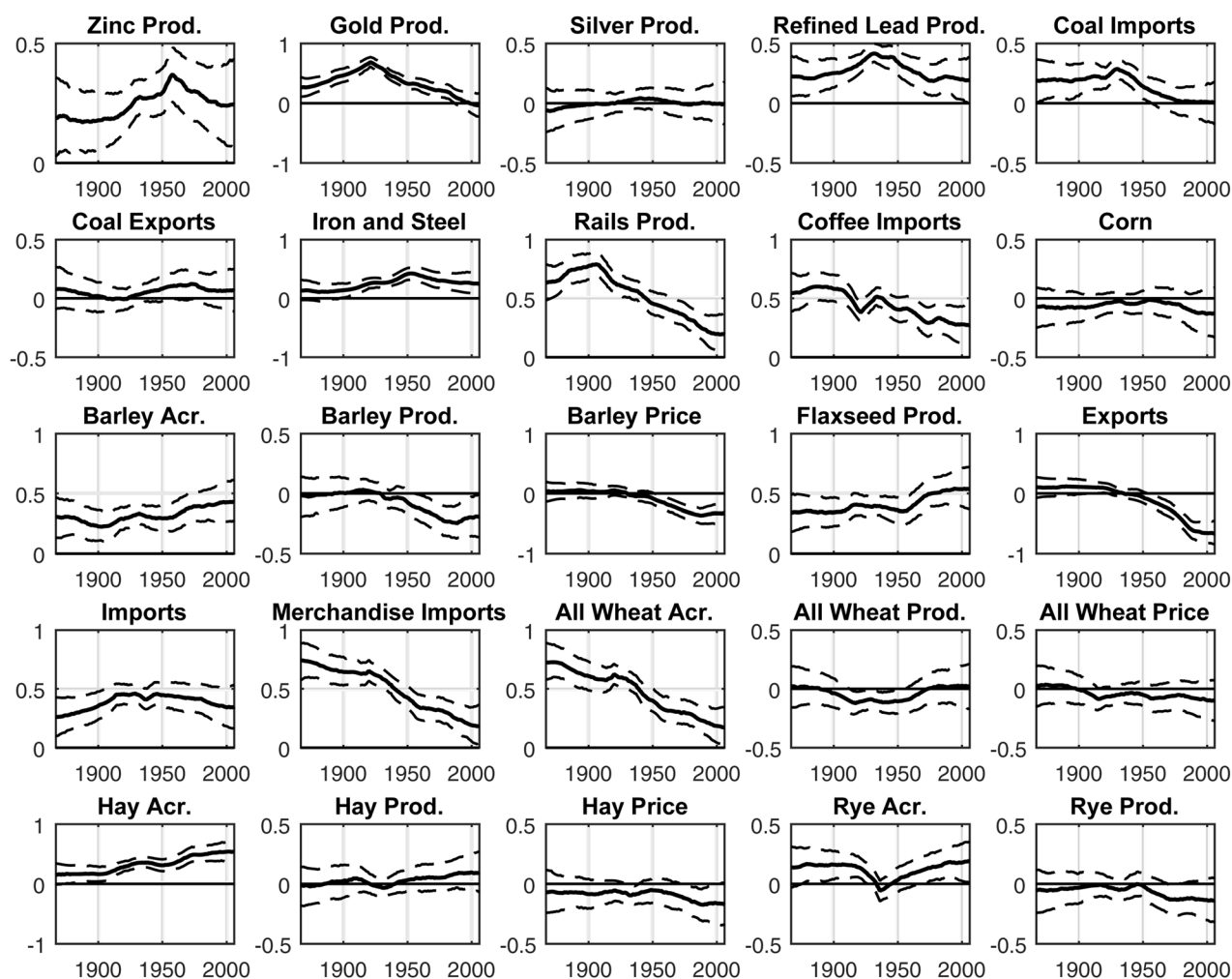
An obvious caveat applies. Underrepresentation of the service sector in our long-term data set is one plausible hypothesis to explain the overall increase in volatility. If services are inherently less volatile than physical output, the secular shift away from agriculture and industry toward services would generate moderation in GDP through a composition effect. Both an aggregation procedure masking this structural shift, as constant factor loadings would do, and lacking representation of service sector data would generate excess volatility. However, we notice that introducing time variation into the factor loadings tends to increase rather than decrease postwar volatility relative to the long-term average. In addition, even in the tertiary sector data that we do have, there is little evidence of postwar moderation, and the 1960s

again come out as less volatile than the Great Moderation of 1980 to 2006.

Results on the nominal series in our data set are again sensitive to assumptions about time variation in factor loadings. A nominal factor under constant factor loadings is akin to a Laspeyres price index. This index would indicate increased nominal volatility in the postwar period. Such evidence would be consistent with Balke and Gordon (1989), who presented a novel GNP deflator that 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 evidence is again not very robust to introducing time variation in the factor loadings. Under time variation in factor loadings, the postwar increase in nominal volatility relative to the gold standard disappears. This would lend renewed support to traditional views of price level volatility under the gold standard. We notice that our nominal factor obtained under time-varying factor loadings tracks and to some extent indeed predicts the CPI (see figure 4).

FIGURE 3.—TIME-VARYING FACTOR LOADINGS, 1867–2006



Part 2. Solid lines represent the posterior mean and dotted lines are the 16th and 84th percentiles.

Still, the overall nominal factor exhibits comparatively little postwar moderation except for the 1960s. This would imply that monetary policy activism since World War II did not do a much better job than the classical gold standard in terms of stabilizing nominal aggregates or prices around trends. This is probably not too surprising, as we find only mixed evidence of postwar stabilization in real variables, leaving little room for monetary policy to explain it. Leaving agricultural prices aside, nominal variables did become less volatile in the postwar period, including in the Great Moderation and even more so in the Golden Age. However, a look at the volatility patterns of the nonagricultural real series under time-varying factor loadings leaves doubts as to whether this nominal stabilization achieved very much in terms of stabilizing the real economy, in an echo of the results of Primiceri (2005).

B. The Role of Stochastic Volatility

Stochastic volatility hitting the model operates through the state equation of the factors. We allow its disturbance

term to follow a random walk and restrict its variance only very mildly. Results for the aggregate factor are shown in figures 5 (top) under time-varying factor loadings and in 5 (bottom) under constant factor loadings.

Figure 5 (top) bears out a hump-shaped pattern of volatility hitting the U.S. economy between 1867 and 2006. The salient feature of this graph is that the Great Depression of the 1930s was not an isolated phenomenon. Volatility had started to increase around the turn of the twentieth century and reached its first peak during the early 1920s. During the 1930s, it began a decline that continued unabated to the end of the millennium. The Great Moderation of the 1980s and 1990s appears only as a temporary, less-than-significant acceleration of this process. Viewed in this perspective, the Great Depression emerges as embedded in a secular event that began before World War I and ended sometime in the 1960s. In contrast to the factor estimates shown above, there was further moderation of macroeconomic shocks after that. We notice in passing that the long-term decline in these shocks all came to an end after 1995, and certainly so in the early 2000s.

TABLE 1.—VOLATILITY COMPARISON, POST-WORLD WAR II/PRE-WORLD WAR I

	1867–1913	1946–2006	Post–World War II/ Pre–World War I	Post–1980/Prewar	1960s/Prewar
A. GDP					
Balke/Gordon GDP-NIPA	2.47	1.85	0.75	0.47	0.40
Romer GDP-NIPA	2.07	1.85	0.90	0.56	0.47
B. All 52 series					
Time varying (mean)	1.48	1.85	1.25	0.75	0.60
Time varying (SD)	(0.22)	(0.00)	(0.19)	(0.18)	(0.14)
Constant (mean)	2.04	1.85	0.91	0.47	0.53
Constant (SD)	(0.17)	(0.00)	(0.07)	(0.08)	(0.10)
C. Nonagricultural Series					
Time varying (mean)	1.58	1.85	1.17	0.72	0.65
Time varying (SD)	(0.25)	(0.00)	(0.19)	(0.22)	(0.16)
Constant (mean)	2.12	1.85	0.88	0.45	0.50
Constant (SD)	(0.16)	(0.00)	(0.07)	(0.07)	(0.10)
D. Real series					
Time varying (mean)	1.77	1.85	1.05	0.56	0.60
Time varying (SD)	(0.28)	(0.00)	(0.17)	(0.18)	(0.15)
Constant (mean)	1.72	1.85	1.08	0.52	0.51
Constant (SD)	(0.02)	(0.00)	(0.01)	(0.01)	(0.01)
E. Nominal series					
Time varying (mean)	1.50	1.45	0.97	0.75	0.40
Time varying (SD)	(0.48)	(0.00)	(0.19)	(0.19)	(0.12)
Constant (mean)	1.09	1.45	1.33	1.03	0.57
Constant (SD)	(0.11)	(0.00)	(0.13)	(0.15)	(0.14)
F. Nonagricultural nominal series					
Time varying (mean)	2.21	1.45	0.65	0.50	0.40
Time varying (SD)	(0.13)	(0.00)	(0.04)	(0.04)	(0.03)
Constant (mean)	2.09	1.45	0.69	0.52	0.42
Constant (SD)	(0.03)	(0.00)	(0.01)	(0.01)	(0.01)

Cyclical components of GDP series obtained from Hodrick-Prescott (6.25)-filter. Prior specification: $\alpha_e = 101$; $\delta_e = 0.1$ in the IG prior on σ_e in equation (5). Volatility of real series standardized to relevant NIPA subaggregates for 1946–2006. Volatility of nominal series standardized to relevant sectoral GDP deflators for 1946–2006.

A somewhat different picture emerges under constant factor loadings (see the bottom panel of figure 5). Here, postwar moderation clearly exists and is an actual departure from an earlier, much more volatile state of the U.S. economy that was only briefly interrupted by a temporary lull in macroeconomic shocks toward the end of the nineteenth century. Even here, the Great Depression looks like a secular phenomenon whose origins go back to before World War I. But it is less unique relative to the nineteenth century.

Drawing the results of this section together, we notice that the patterns in figure 5 (top) broadly correspond to the volatility patterns in table 1. This is reassuring, as our factor estimate under time-varying factor loadings assigns much reduced levels of volatility to both the factor estimate and the stochastic volatility term for the classical gold standard. Conversely, the much higher volatility levels from 1867 to 1913 for the factor under constant loadings are reflected in higher stochastic volatility as well. This is consistent with our interpretation that much of the disappearance of postwar moderation in our estimates is due to the substantial downward revision of volatility we find for the period of the gold standard before 1914.

IV. 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 data set 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) suggest the increase was much weaker. The discrepancy between their findings is partly related to the recession of 1920–1921, which is rather mild in Romer's data. In contrast, Balke and Gordon (1989) report a more severe slump.

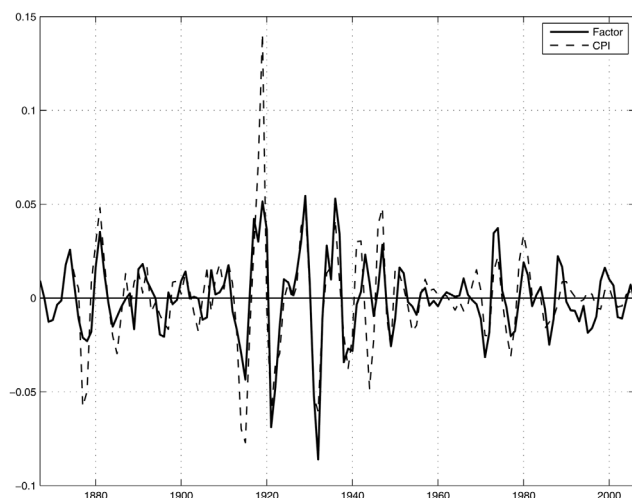
We repeat the above exercise for the subperiods from 1867 to 1929 and 1867 to 1939 with the wider data set of 98 series. To maintain comparability, we also reestimate the factor model with the narrower data set of 52 series employed in the previous section. Because time variation in the aggregation procedure played such a central role in the previous section, 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 an HP(6.25) filter. Figure 6 shows the cyclical components in both series alongside the factors from 1867 to 1929. Comparisons with 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.

TABLE 2.—VOLATILITY ACROSS WORLD WAR II, 52 SERIES, 1867–2006: TIME-VARYING AND CONSTANT FACTOR LOADINGS

Deviation from HP Trend %	1867– 1913	1914– 1929	1930– 1939	1946– 2006	1946– 1959	1960– 1969	1970– 1984	1985– 2006	Postwar/ Prewar	Post–1984/ Prewar	1960s/ Prewar
Romer GNP	2.07	2.78	5.62	1.86	2.79	0.98	2.06	1.16	0.90	0.56	0.47
Balke/Gordon GNP	2.47	4.10	5.62	1.86	2.79	0.98	2.06	1.16	0.75	0.47	0.40
All 52 series											
TV	1.48	3.92	5.48	1.85	2.60	0.88	2.10	1.50	1.25	1.02	0.60
C	2.04	5.54	7.35	1.85	2.90	1.08	2.04	1.12	0.91	0.55	0.53
Nonagricultural series											
TV	1.58	3.99	5.68	1.85	3.08	1.03	1.79	1.12	1.17	0.71	0.65
C	2.12	5.29	7.09	1.85	3.13	1.07	1.80	1.01	0.88	0.47	0.50
Agricultural series											
TV	1.48	3.31	6.37	1.85	2.28	1.01	2.23	1.62	1.25	1.08	0.61
C	1.48	2.73	4.79	1.85	1.78	0.80	2.54	1.79	1.25	1.20	0.54
Real series											
TV	1.77	3.98	5.44	1.85	3.02	1.08	1.88	1.08	1.05	0.61	0.60
C	1.72	3.60	3.92	1.85	3.43	0.88	1.54	0.80	1.08	0.47	0.51
Nonagricultural real series											
TV	1.14	2.77	3.99	1.85	2.63	1.07	1.94	1.51	1.63	1.32	0.93
C	2.44	5.10	6.94	1.85	2.81	1.05	2.21	1.03	0.76	0.42	0.43
Agricultural real series											
TV	1.41	2.70	5.18	1.85	2.23	1.74	2.30	1.28	1.32	0.88	1.24
C	0.82	2.06	4.34	1.85	2.00	1.74	2.43	1.40	2.26	1.70	2.13
Nonagricultural real physical series											
TV	1.07	2.61	3.74	1.85	2.66	1.26	2.17	1.08	1.73	1.03	1.20
C	2.41	5.15	7.01	1.85	2.83	1.05	2.20	1.01	0.77	0.42	0.43
Nonagricultural real nonphysical series											
TV	0.82	2.24	2.19	1.85	2.78	1.07	1.00	1.40	2.25	1.63	1.18
C	0.69	1.86	1.72	1.85	2.92	0.67	0.75	1.31	2.68	1.70	0.95
Nominal series											
TV	1.50	3.79	4.35	1.45	1.41	0.61	2.02	1.34	0.97	0.88	0.40
C	1.09	3.11	3.77	1.45	1.33	0.61	2.08	1.34	1.33	1.23	0.57
Nonagricultural nominal series											
TV	2.21	4.41	4.96	1.45	1.97	0.88	1.83	1.01	0.65	0.45	0.40
C	2.09	4.41	5.03	1.45	2.00	0.88	1.82	0.98	0.69	0.47	0.42
Agricultural nominal series											
TV	1.34	2.62	3.32	1.45	1.34	0.67	1.97	1.42	1.08	1.06	0.49
C	1.20	2.49	3.38	1.45	1.34	0.65	2.00	1.41	1.21	1.18	0.54

TV = time-varying factor loadings; C = constant factor loadings. Time-varying factor loadings model and constant factor loadings model both include the stochastic volatility component in the factor equation. Prior specification: ($\alpha_k = 101$ and $\delta_k = 0.01$) and ($\alpha_\eta = 11$ and $\delta_\eta = 0.01$).

FIGURE 4.—TVAR FACTOR FROM SEVENTEEN NOMINAL SERIES VERSUS U.S. CPI



CPI data are deviations from HP(6.25) trend. Factor standardized to standard deviation of CPI (1947–2007). CPI annualized and shifted forward by one year.

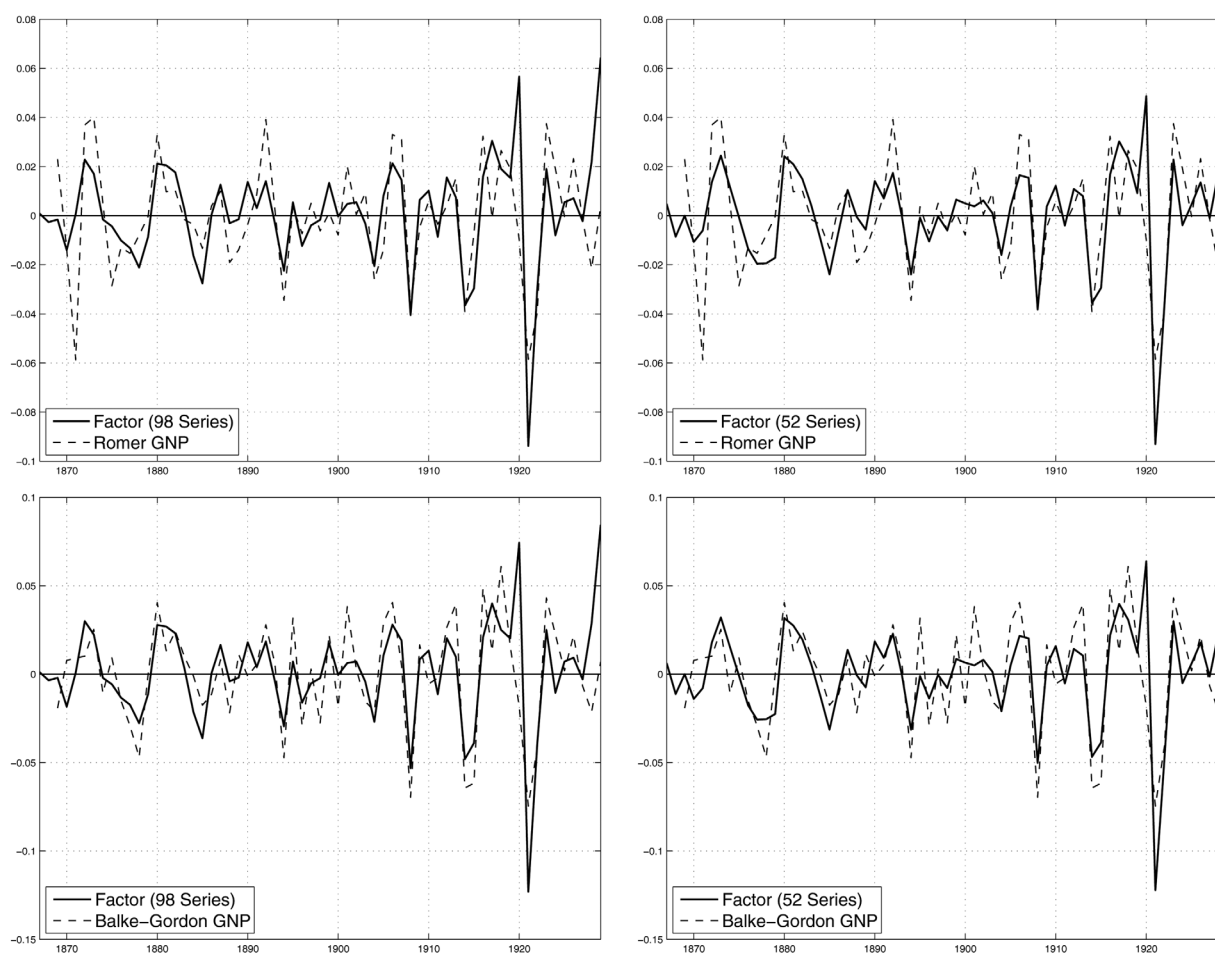
This comparison yields two insights. For the pre-1914 period, the Romer estimate of GDP seems to be more in line with our factor estimates than the Balke and Gordon estimate. For the period from 1914 to 1929, our factors are

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 industrial production by Miron and Romer (1990).

Table 3 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. Because 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 two different approaches, each estimating the factors over a different time span. Under the first approach, the factor is estimated for the whole period to 2006 and its volatility calibrated to NIPA for 1946 to 2006. This is the same strategy adopted in table 1. Results are shown

FIGURE 5.—THE U.S. BUSINESS CYCLE, 1867–1929, FACTOR VERSUS GNP ESTIMATES



TVAR factors from 52 and 98 series, respectively. GDP data are deviations from HP(6.25) trend.

in panel A of table 3. 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 (panel B). As we have more series available for this subperiod, we conduct this experiment twice—once for the same 52 series that are available through 2006, the second time for the wider data set of 98 series. This strategy also underlies figure 6. Results are shown in the panel A of table 3.

Because the factor estimates are not recursive, truncation of the estimation period affects the results for all subperiods. Truncating to 1867 to 1929, the period of interest in this section, makes for an unbiased comparison of volatilities across World War I. Extending the estimation period to 2006 risks introducing bias but permits calibrating the factors to the volatility of the official NIPA data. As a consequence, volatility in the pre-1929 years can then be directly compared to volatility in the NIPA series for relevant subperiods.

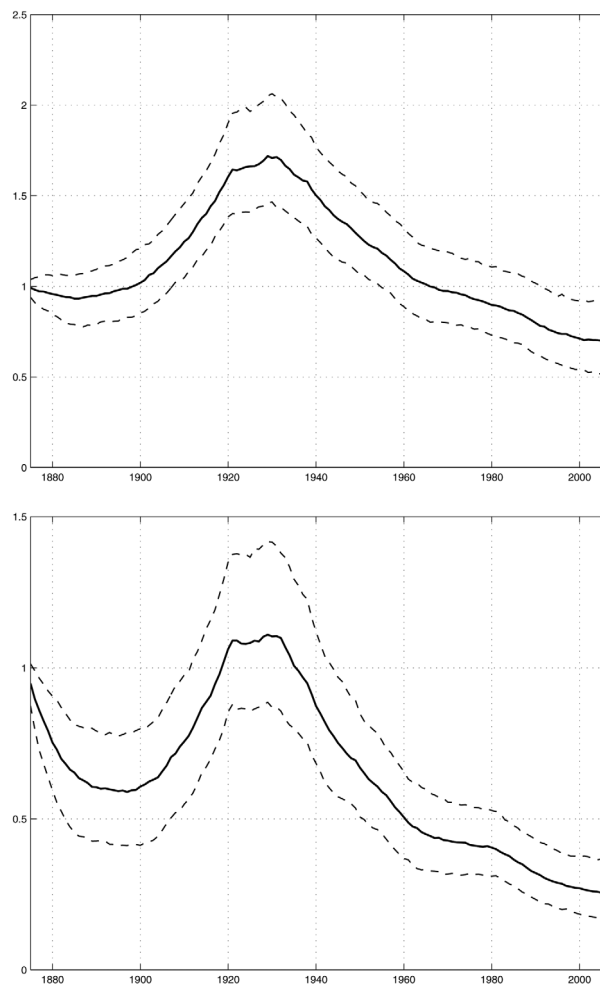
Three results stand out from these robustness checks. First, the increase in factor volatility across World War I consistently comes out higher than in existing GDP estimates (table 3, last column). This result is robust to truncations

of the estimation period, as well as to widening the database for the factor estimate from 52 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 and Gordon estimate would suggest (table 3, 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 the factor estimates calibrated to NIPA. In both cases, prewar volatility is close to the postwar level of volatility (1.85; see table 1) and in many cases markedly lower. The third main result is that volatility during 1914 to 1929 (second column in table 3) is consistently higher than estimated by Romer (1989) and is indeed close to or even higher than in the Balke and Gordon (1989) data.

V. The U.S. 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

FIGURE 6.—STANDARD DEVIATION OF THE RESIDUAL OF THE FACTOR EQUATION, 1867–2006



Solid lines represent the posterior mean, and dotted lines are the 16th and 84th percentiles. The upper panel shows results from a factor model with time-varying factor loadings and stochastic volatilities. The lower panel depicts results from a model with constant factor loadings and stochastic volatilities.

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. Alternative estimates by Kuznets (1961) and Kendrick (1961) show less volatility than NIPA for 1939 to 1945. These income-based estimates also suggest a less pronounced increase in economic activity, as well as a different business cycle chronology.¹² The very large business cycle swings during World War II implied by the NIPA data have generated renewed interest because of their implications for the size of the fiscal multiplier (see Blanchard & Perotti, 2002; McGrattan & Ohanian, 2010; Ramey, 2011). 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).

In figure 7, the upper panel plots the factor against the official NIPA accounts. The income estimate of Kuznets (1961)

TABLE 3.—VOLATILITY COMPARISON ACROSS WORLD WAR I, 1867–1929/1939

Deviation from HP(6.25) Trend	1867–1913	1914–1929	1930–1939 (NIPA)	1914–1929/ 1867–1913
GNP estimates				
Romer	2.07	2.78	5.62	1.34
Balke-Gordon	2.47	4.10	5.62	1.66
A. 1867–2006 Data Set, Normalized to NIPA, 1946–2006				
Factor 52 series				
Time varying (mean)	1.48	3.92	5.48	2.66
Time varying (SD)	(0.22)	(0.48)	(0.60)	(0.22)
Constant (mean)	2.04	5.54	7.35	2.71
Constant (SD)	(0.17)	(0.38)	(0.50)	(0.18)
B. 1867–1929 Data Set, Normalized to Balke-Gordon, 1867–1929				
Factor 52 series				
Time varying (mean)	1.88	5.01		2.66
Time varying (SD)	(0.11)	(0.13)		(0.22)
Constant (mean)	1.86	5.03		2.71
Constant (SD)	(0.09)	(0.10)		(0.18)
Factor 98 series				
Time varying (mean)	1.86	5.03		2.70
Time varying (SD)	(0.10)	(0.11)		(0.21)
Constant (mean)	2.03	4.83		2.38
Constant (SD)	(0.06)	(0.08)		(0.11)

Cyclical components of GDP series obtained from Hodrick-Prescott (6.25) filter.

is shown in the lower panel. Data are again detrended by an HP(6.25) filter.

The factor estimate shown in this figure is obtained from 35 real series, identical to those examined in table 1 (panel C). 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's income estimate (in passing, we note the earlier trough of the Great Depression implied by the factor). At the beginning of the war, however, the factor tracks the Kuznets estimate much more closely than the Commerce series on which the wartime NIPA data are based, rising quickly from the trough in 1938 until 1941.

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 Kuznets aggregate has its lower turning point. From the peak of war production, the economy according to NIPA fell into a deep recession that lasted until 1949 while, according to Kuznets, a short-lived postwar boom set in with a summit in 1946.

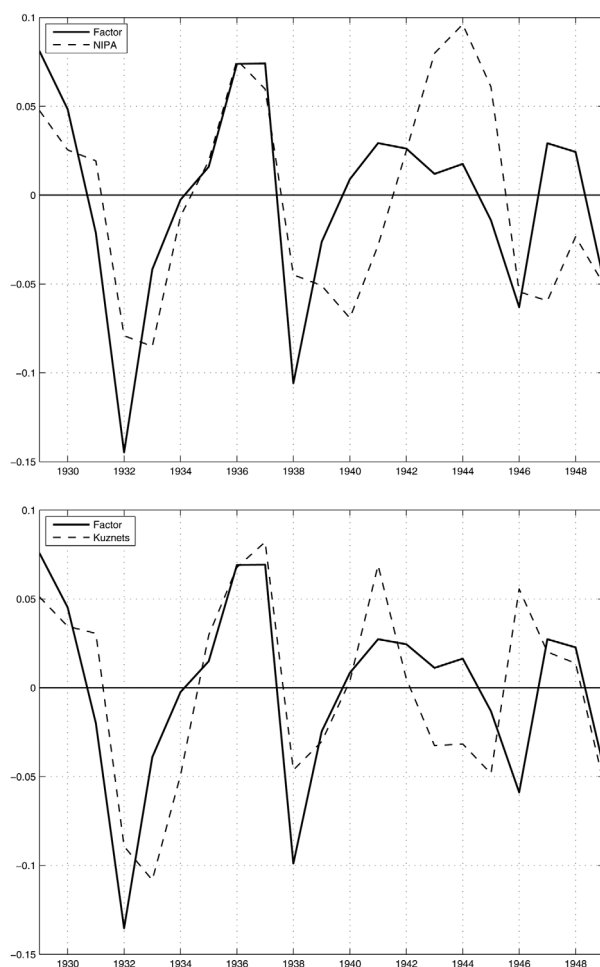
There is a wide gap between these rivaling business cycle estimates in timing and volatility, but our real factor may represent a reasonable compromise. While it leans toward Kuznets's alternative series until 1941, subsequently it deviates by leveling off smoothly rather than crashing. After 1941 it matches NIPA's timing with a short hiccup in 1944 and a postwar trough in 1946. The short postwar revival, however, rather favors Kuznets's series again.

Search for deeper reasons for this discrepancy must be left for future work. Methodological differences in accounting for war output, as well as weighing issues in the construction of the deflator, may have played a role.¹³ However, we note

¹² For a discussion, see Kuznets (1945), Mitchell (1943), and Nordhaus and Tobin (1972) and a review in Higgs (1992, p. 45).

¹³ See Kuznets (1952) for further discussion and Carson (1975) for details on the debate.

FIGURE 7.—TVAR FACTORS FROM THIRTY-FIVE REAL SERIES VERSUS RIVALING ESTIMATES OF GNP DURING WORLD WAR II



GDP data are deviations from HP(6.25) trend.

that the factor drawn from 35 real series in figure 7 and the broader factor drawn from 52 series, 17 of them nominal, in figure 1, 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 estimates of wartime output and income.

Summing up, World War II is the one period where our factor exhibits marked deviations from the official NIPA business cycle timing. However, this reflects an important debate in U.S. business cycle historiography, which could hitherto not be resolved yet. The cyclical behavior of our real factor offers a compromise estimate and may help reconciling Kuznets's revisionist estimate with the official historiography of the American business cycle during World War II.

VI. Conclusion

Postwar moderation in the U.S. business cycle has been elusive so far, and probably never existed. In this paper,

we reexamined business cycle volatility since 1867 using a dynamic factor model. Based on a large set of disaggregate time series, we obtained factors representing economic activity at the aggregate level and for the nonfarm economy and employed them to compare volatility across World War I as well as in the long run.

One 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 perhaps also less volatile than the postwar business cycle. We also find pervasive evidence that the increase in business cycle volatility across World War I was even larger than has been maintained in previous research. Aggregate shocks to the U.S. economy, which we measure by stochastic volatility, followed a distinct hump-shaped pattern during the nearly 140 years we study. The anomalies culminating in the Great Depression of the 1930s became visible in the early 1900s.

This also has implications for the postwar period. In a process that started in the 1930s and petered out with the Great Moderation of the 1980s and 1990s, aggregate shocks to the U.S. economy gradually weakened, probably undercutting the levels of the late nineteenth century by the 1960s. However, this did not immediately translate itself one-to-one into reduced volatility of economic activity, due largely to a long-term sectoral shift away from agriculture toward more volatile industries.

For the years surrounding World War II we find indications that the standard figures for national output may misrepresent the business cycle turning points and that both the wartime boom and the postwar bust of the U.S. 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).

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 employ 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 obtain results for constant factor loadings, as well as under informative priors allowing for gradual time variation in the factor loadings. Our findings suggest that once time variation is introduced, results are clear-cut and indicate that the postwar U.S. business cycle was probably more, not less, volatile than during the gold standard era before World War I.

Our findings are related to earlier work that was based on backward extrapolations of national accounts into the late nineteenth and early twentieth century, but whose conclusions on postwar moderation seemed mixed. Our approach can be viewed as a way to provide an independent validation that is based on a different methodology and a wider data set.

While there seems to be little evidence of postwar moderation overall, we do reproduce the standard evidence on the Great Moderation of 1980–2006, as well as the even

lower volatility of the Golden Age of the 1960s. Within the inevitable limits of a long-term comparison, we find that for some subsectors of our data set, volatility during the Great Moderation was markedly lower than before 1914. Volatility was almost uniformly lower than during the gold standard during the 1960s Golden Age.

We conclude on a skeptical note regarding postwar monetary stabilization. For the nonfarm economy, we find substantial postwar smoothing of the nominal series relative to the gold standard, very visibly so during the Great Moderation and the earlier Golden Age. However, the evidence on postwar stabilization in the real economy remains mixed. Postwar monetary policy no doubt attempted to stabilize the U.S. economy. But beyond the visible moderation of price volatility itself, stabilization of the real economy since the postwar period remains elusive.

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