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Abstract

This article investigates conditional growth volatility for industrial production in the U.S. during the 1791-1915 period, taking as a reference the index constructed by Davis (2004). The period includes the major negative shock represented by the Civil War with the associated resource allocation distortions. The evidence suggests persistence in conditional volatility as would be found in later studies for the U.S. on GDP growth volatility. However, there is no evidence of an asymmetric volatility response to economic events despite an especially negative shock within the sample period.

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Keywords: growth volatility; industrial production; EGARCH model

1 Introduction

The impact of significant negative shocks on economic activity has attracted recurring interest in the economic literature. In particular, the disruptive effects of the U.S. Civil War in the 19th century have been scrutinized from distinct perspectives. Goldin and Lewis (1975) attempt to quantify direct and indirect costs associated with human and physical capital losses. The latter were more substantial in the South, although the data are less precise than in the Union case. For indirect costs, counterfactual exercises were carried out by assuming that pre-war growth trends would have prevailed in the absence of war, and thus, some exploratory estimates for consumption loss can be obtained. In any case, the extent of such a negative shock was dramatic, and the direct cost only appears to capture 45% of the costs. It is clear that such a dramatic negative shock had considerable consequences in terms of allocation of resources that reflect, for example, aspects pertaining to labour mobility and redirection of workplace organization to the war effort. Even though the destruction of industrial establishments, which were concentrated in the North, was less severe than in the South, the impacts of the war on resource allocation cannot be overlooked. In fact, Khan (2016) highlights the negative and significant effect on innovation that distortions in the labour and capital markets had. In the case of military innovations, the outcome in terms of patents between 1855 and 1870 was positive. However, in the case of non-military applications, the related outcomes were weak, especially within the war sub-period. In contrast to other contributions in the literature, the author contends that the net effect of the misallocation of resources during the Civil War was most likely negative in terms of its impact on innovation, which was mostly associated with limited mobility for innovating entrepreneurs and low return on non-military innovations.

The unfavourable trajectory of productivity in the U.S. during the 1860s can be put in perspective through a comparative assessment with the United Kingdom as considered by Broadberry and Irwin (2006) for the 19th century. Aggregate and sectoral labour productivity analyses build on previous works by Broadberry (1994, 1998). The evidence indicates that since 1840, the U.S. had greater labour productivity than in the U.K. In contrast, in agriculture, productivity was nearly the same in both countries, while in the services sector the U.K. displayed some dominance in productivity. In aggregated terms, both labour productivity and per capita income were greater in the U.K., which reflects to some extent the greater share of the U.S. workforce being allocated to low value-added activities in agriculture. In fact, the relative dominance of the U.S. in aggregated terms would only become clear by the 1890s.

Moreover, it is worth noting that a strand of the literature on growth volatility highlights underlying factors associated with productivity. Stiroh (2009) considers aggregate and sectoral movements in productivity and contends that the ability of the labour market to adjust to shocks can affect growth volatility. In particular, the increasing flexibility of the labour market appears to have had an important positive impact on productivity after 1984. The interplay of labour market shock absorption and productivity is suggestive in the context of extreme economic disarray, as would be the case in a civil war, and can produce non-negligible effects on growth volatility.

In addition to the trajectory of productivity, as associated with economic shocks, it is pertinent to assess possible asymmetric growth volatility. In fact, such asymmetric response to positive and negative shocks may reflect a combination of larger risk aversion in the case of negative events, heterogeneous expectations, supply side restrictions and savings for precautionary motivations [see Ho et al. (2013)]. Thus, a handful of papers have investigated asymmetric conditional volatility of growth for more recent periods, such as French and Sichel (1993) for the U.S. on real GNP; Hamori (2000) for Japan, the United Kingdom, and the U.S. on real GDP; Ho and Tsui (2003, 2004) for, respectively, Canada and the U.S. and Greater China in the case of real GNP; and Ho et al. (2013) for selected OECD countries. The evidence, which is mostly based on similar exponential GARCH (EGARCH) models with distinct datasets, is mixed. In the specific case of the U.S., significant asymmetry on growth volatility is emphasized by Ho and Tsui (2003) and Ho et al. (2013). Similar evidence, obtained by French and Sichel (1993), is particularly suggestive, as a breakdown in terms of larger sectors indicates that asymmetry emerges in the cyclically sensitive sectors and is therefore relevant to contrast between aggregate and sector-specific shocks.

Similar analyses for the 19th century, which was marked by an especially disrupting negative shock, can benefit from increasingly reliable datasets as exemplified by Miron and Romer (1990), Calomiris and Hanes (1994) and Davis (2004), with the latter two contributions encompassing the Civil War period.

The study of conditional growth volatility when an economy is subject to significant shocks can be appealing. Moreover, if disruptive negative real GDP shocks induce greater future volatility than positive shocks of the same magnitude, this may further justify the need for macroeconomic stabilization measures.

The paper is organized as follows. The second section discusses the main databases for the activity level in the U.S. economy that include the 19^{th} century and outlines the empirical strategy for assessing asymmetric growth volatility. The third section presents and discusses the empirical results. The fourth section includes some final comments and concludes the paper.

2 Empirical strategy

2.1 Historical series for economic activity in the U.S.

The quantitative assessment of different business cycle features in the 19th century has benefited from the increasing availability of more consistent and reliable time series. It is worth mentioning at least 3 datasets that include periods in the 19th century. Miron and Romer (1990) present a monthly index for industrial production during the period from 1884-1940, whereas Davis (2004) constructs an annual index for industrial production during the 1790-1915 period; Calomiris and Hanes (1994) construct an annual index covering the 1840-1914 period. The importance of those indices is clear, as the Federal Reserve Board-FRB began providing a reliable index for industrial production only in 1919. In fact, prior to 1919, the conventional indices had several problems and limitations. In particular, the dependence on nominal variables and the scarcity of relevant component series led to an inaccurate depiction of the business cycle.

Broadly speaking, those indices shared the same methodological concerns in terms of focus on component series reflecting actual output or a related direct proxy of physical quantity, excluding nominal indicators, while relying on long series to assure consistency and avoid comparability issues during the sample period. The individual series were then aggregated into a single industrial production index considering as weights the value added corresponding to a specific component series along the lines of the procedure adopted by the FRB.

Davis (2004) contends that despite the significant weight of the agrarian sector in the U.S. economy in the 19th century, it is relevant to advance the careful construction of an industrial production index, as it would be relevant for portraying the historical evolution and the gradual emergence of the U.S. as an economic power following the industrialization process. Moreover, even then, industrial production had important interconnections with agriculture, construction and retail.

The index advanced by Miron and Romer (1990) is constructed using monthly consistent series for physical production in terms of 13 industrial products and minerals. The data span the 1884-1940 period and are intended to cover the WWI period and the later interwar period while allowing for comparisons with the figures generated by the FRB from 1919 onwards. Among the most representative industries, one can mention those related to industrialized food, textile products, iron, ore, coal and oil products. On the other hand, it is worth noting the absence of industries related to forestry products, glass and clay. The advantages of the index reflect its reliance on physical products, which means it is not subject to distortions accruing from prices and foreign trade volumes. Moreover, the authors highlight the consistency of the series without gaps that usually tend to be solved by questionable interpolation procedures.

However, the downside of seeking complete component series to ensure consistency relates to the omission of new information in a changing economy. In fact, as argued by the authors, the omission of new products with incomplete series would lead to some underestimation of industrial production growth as new products tend to experience faster growth.

Moreover, the use of physical shipments instead of physical production itself can lead to a discrepancy between the index and actual aggregate economic activity. In fact, such bias could make the index more sensitive to cyclical effects since primary commodities are more volatile than highly processed products as stressed by the aforementioned authors.

More recently, Davis (2004) constructed an annual industrial production index for the U.S. during the 1790-1915 period by considering 43 annual series based on physical quantities of manufacturing and mining. The purpose was to fill a gap in the literature prior to the WWI period, especially in the antebellum period. A distinctive feature of Davis´s index is that more than half of the series used were not previously considered because the data were not available or were difficult to access. The author completed a careful data collection by accessing private sources such as trade publications, firms' registries and studies on firms, among others. New annual series for industrial productions were compiled for a variety of final industrial products, such as steam propelled fire engines, naval ships, firearms, musical and scientific instruments, watches and clothing items. For the conventional series, data were collected from government sources with occasional extensions and refinements as in the case of locomotives, merchant ships and pig iron. It is worth mentioning that more than 60% of the index composition comes from private sources, whereas in the case of the FRB, those accounted for 25% of the composition. Moreover, Davis (2004) indicates that approximately 25% of the series are indirect proxies for final products, whereas in FRB, the related figure reaches 50%.

The construction of the aggregate production index upon individual series involved the attribution of weights. Census reports with industry-level value added figures were taken as a reference. Thus, the most accurate and feasible portrayal of the industrial structure in the antebellum period given the absence of information for that period in the literature was a priority. Additionally, it was important to consider the evolution of the industrial composition between the Civil War and World War I. An adopted solution was to consider distinct base periods before and after the Civil War to allow the incorporation of products that were not previously available before the 1850 census. Moreover, it was possible to update the product basket with information from fast growth industries to the postbellum period without affecting the comparability during the index period. Such a procedure allows the portrayal of changes in the relative importance of components in the U.S. industrial structure and the appearance of new products before and after the Civil War and is not subject to the growth underestimation critique associated with the index of Miron and Romer (1990).

Davis (2004) makes additional comparisons with other indices, especially Frickey (1947) (an annual manufacturing index) and Miron and Romer (1990). Despite the similarities between those indices, which reflect some crucial common components such as pig iron and cotton textiles, there are several notable discrepancies in terms of volatility.

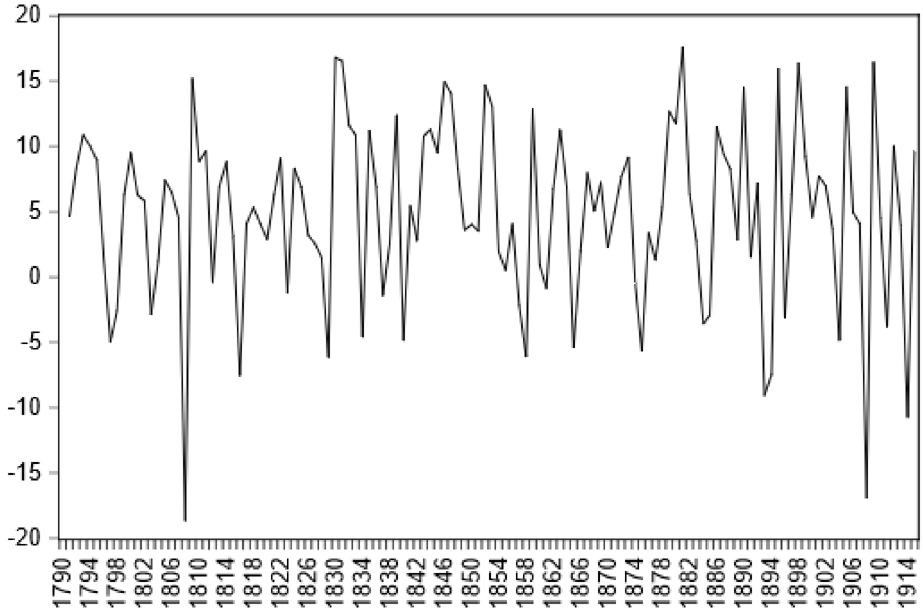
From a comparative perspective, in the industrial production index by Davis (2004), related growth volatility is smaller than the other alternatives in terms of the standard deviation, and therefore, cyclical fluctuations appear to be less intense. Thus, a newer index would be less prone to criticism, as conventional series for industrial production in the postbellum period were often disputed for overestimating business cycle fluctuations. In particular, Romer (1986) emphasizes that when Frickey´s index is extended and compared to the index produced by the FRB, it generates excessively volatile data. The index advanced by Davis (2004) is qualitatively distinct from other indices as its sample includes fewer raw materials and intermediate goods and more final products than the indices by Frickey (1947) and Miron and Romer (1990). Thus, the index is less volatile and less dependent on primary commodities while incorporating more complex products.

Calomiris and Hanes (1994) constructed an annual industrial production index for both the antebellum and postbellum period that is in line with Frickey´s index, the index from the FRB for the 20th century; their index includes 7 annual series, such as pig iron production and cotton consumption, among others.

Calomiris and Hanes (1994) note that several authors had utilized trend deviations in Frickey's index (1947) in order to assess the business cycle in the postbellum period. The aforementioned authors had chosen weights for deviations in individual series based on that index. However, Davis (2004) criticizes the index by Calomiris and Hanes (1994) on the grounds that their methodology would not allow a direct inference on volatility changes before and after the Civil War, since the antebellum data would have been artificially constructed to replicate the index by Frickey (1947) for the postbellum period. The imposition of postbellum productivity patterns for the antebellum period is questionable.

In sum, the previous discussion indicates important advantages of the industrial production index constructed by Davis (2004) for the 1790-1915 period. The present study focuses on growth volatility that will be considered in terms of the first difference in natural logs multiplied by 100 as depicted in Figure 1 for the 1791-1915 period. The corresponding summary statistics are reported in Table 1. The negative skewness indicates larger probability associated with contraction, whereas the leptkurtic character of the distribution suggests that extreme changes in the series have high probability. Additionally, the normality test by Jarque and Bera (1987) capture possible departures from normality associated with the third and fourth moments of the distribution and suggests a non-normal distribution for U.S. growth in industrial production.

Figure 1
Growth in U.S. Industrial Production – 1791-1915



Source: authors´s elaboration upon Davis (2004)

Table 1
Growth in U.S. industrial production, 1791-1915 – Summary Statistics
[No. of observations: 125]

Mean	4.897
Median	5.336
Maximum	17.611
Minimum	-18.669
Standard deviation	6.831
Skewness	-0.667
Kurtosis	3.775
Jarque-Bera test for normality	12.400 (0.002)

Note: p-value is reported in parentheses

The primary issue in the present paper is the assessment of conditional growth volatility with a research question centred around possible asymmetric patterns following important negative shocks. In fact, previous evidence has analysed unconditional volatility and assessed the fluctuations of business cycles before and after the Civil War. Calomiris and Hanes (1994) conclude that the volatility of industrial production was probably higher before the Civil War than after it. As previously mentioned, Davis (2004) questions the validity of this result because postbellum productive relationships were imposed on the antebellum economy. In his paper, Davis (2004) tests a series of hypotheses of the equality of the mean and variance of the growth rates of industrial production, treating the Civil War as a break-point since it was the major disruptive economic shock in the U.S. during the 19th century. His findings suggest that there was no statistical evidence that fluctuations in U.S. industrial production differed before and after the Civil War. The variance comparison tests do not reject the null hypothesis of equality of growth rate variance. The standard deviation tends to be lower in the antebellum period, but the differences are not statistically significant.

Finally, it is important to note that the possibility of time-varying volatilities can provide a strong motivation for studying conditional volatility models. In particular, the possibility of asymmetric response to economic shocks requires the consideration of a specific model within that class of models, as discussed next in section 2.2.

2.2 Asymmetric volatility: empirical strategy

The seminal paper by Engle (1982) has given rise to a vast literature on Autoregressive Conditional Heteroskedasticity (ARCH) models with several variants accommodating different degrees of persistence and asymmetry in the data [see Bera and Higgins (1993) and Bollerslev et al. (1994) for overviews]. Those models for conditional volatility aim to address salient stylized facts that are present in different economic series. In particular, unconditional distributions that possess thick tails, time-varying variances and large (small) changes that tend to be followed by large (small) changes of either sign provide important motivation for conditional volatility models in the ARCH class. Thus, rather than being restricted to descriptive unconditional analysis for growth volatility as considered in the related empirical literature, it is relevant to proceed with conditional volatility models. A potential shortcoming of the usual generalized ARCH (GARCH) advanced by Bollerslev (1986) relates to the assumption that lagged error terms, either positive or negative, exert a symmetric effect on volatility. However, Nelson (1991) notes its inadequacy for modelling phenomena where a leverage effect prevails, with negative shocks leading to larger future volatility than would be implied by positive shocks of the same magnitude. Thus, he advanced the exponential GARCH model (EGARCH) to allow asymmetric responses to shocks. The model comprises one mean equation and one variance equation. In our present application, we consider an ARMA(p,q)-EGARCH(1,1) specification that embodies a parsimonious EGARCH(1,1) specification along the lines of the previous studies on growth conditional volatility as given by Hamori (2000) and Ho and Tsui (2003, 2004), which can be described as follows in terms of a specific notation for growth in industrial production (IP) defined as $r_t = [\ln(IP_t/IP_{t-1})]*100$:

Mean equation

$$r_t = \pi_0 + \sum_{i=1}^{p} \pi_i r_{t-i} + \varepsilon_t + \sum_{j=1}^{q} \theta_j \varepsilon_{t-j} \qquad (1)$$

Variance equation

$$\log(\sigma_t^2) = \omega + \alpha\left[\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| - \sqrt{\frac{2}{\pi}}\right] + \gamma\left(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right) + \beta \log(\sigma_{t-1}) \qquad (2)$$

The model allows for capturing persistent volatility as indicated by parameter β and most importantly asymmetric volatility if parameter γ is deemed significant in the estimation.

All estimations were implemented in Eviews (version 9.5). In the original contribution by Nelson (1991), it is assumed that the error term follows a Generalized Error Distribution (GED), whereas such software also allows for the consideration of alternative distributions such as a normal or a Student's *t*-distribution. The choice of the orders for the ARMA(p,q) can be based on information criteria. Moreover, different diagnostic tests pertaining to normality, stationarity and serial dependence can be carried out to achieve greater confidence in the estimated model. The more parsimonious specification in terms of an EGARCH(1,1) had been defended in previous applications by Hamori (2000) and Ho and Tsui (2003, 2004) on the grounds that it would place no restrictions on the parameters α, γ and β in the variance equation indicated in (2) and renders the estimation more tractable.

3 Empirical Results

The main estimation results appear in Table 2

Table 2
Estimation results of ARMA (p, q)–EGARCH (1, 1) model

Parameters	**Estimates**	**p-value**
π_0	4.835	0.000
ω	0.454	0.000
α	-0.268	0.000
γ	0.030	0.739
β	0.938	0.000
Bayesian Information Criterion (BIC)		**6.739**

Prior to inspecting such a table, it is important to consider unit root tests [Augmented Dickey-Fuller-ADF and Phillip-Perron-PP tests], given the ARMA specification for the mean equation.[1] The corresponding evidence, presented in Table A1 in the appendix, suggests that the growth in industrial production is I(0), as would be expected.

A second preliminary test pertains to the assessment of the prevalence of ARCH effects prior to the model estimation. For that purpose, we consider the Q statistic by Ljung and Box (1979) to jointly evaluate the autocorrelations upon a given order as applied to the squared values of the series. The autocorrelations for lags 1 and 2 had Q statistics of 6.430 (p-value = 0.011) and 7.710 (p-value = 0.021), and the following lags were not significant at the 5% level. Thus, the evidence suggests that ARCH effects are potentially relevant.

Now, we can turn to the estimation of the ARMA(p,q)-EGARCH(1,1) model. The selection of the order for the ARMA(p,q) model was based on the usual Bayesian Information Criterion (BIC) by Schwarz (1978). Such a criterion favours parsimonious specifications. In the present application, it suggests an ARMA(0,0) specification, where the mean is white noise plus a constant. Table 3 presents diagnostic tests pertaining to normality and ARCH structure in residuals. We take as a reference the usual criterion of a 5% significance level; thus, the evidence favours the non-rejection of the null hypothesis of normality of the standardized residuals. Similarly, the diagnostic tests for ARCH

[1] See Dickey and Fuller (1981) and Phillips and Perron (1988).

effects are satisfactory, as those are not significant and therefore do not indicate structures in the residuals that could suggest misspecifications in the model.

Table 3
Diagnostic Tests for Standardised Residuals

Test	Test Statistic	p-value
Jarque-Bera test for normality $[\chi^2(2)]$	4.853	0.088
LM Test for ARCH effects (4 lags) $[[\chi^2(4)]$	5.200	0.267
LM Test for ARCH effects (8 lags) $[[\chi^2(8)]$	7.487	0.485

Having gained additional confidence in the estimated ARMA(0,0)-EGARCH(1,1), we can highlight some salient results accruing from the estimation. If one considers the aforementioned significance level, the constant in the mean equation is significant, and thus, one faces a simple white noise process plus a constant. For the variance equation, on the other hand, the case for a highly persistent conditional variance is indicated by the large and highly significant coefficient of β. A similar result was obtained by Ho and Tsui (2003) in the context of GDP growth volatility in the U.S. for a recent period. Other coefficients pertaining to the variance equation, such as ω and α, are significant at the 1% level.

Finally, the parameter γ is of particular interest in the present article as it allows for detection of asymmetric responses to shock on conditional growth volatility. However, the corresponding p-value of 0.739 does not favour the existence of asymmetric volatility, indicating that there is no statistical evidence that negative shocks induce greater future volatility than positive shocks of the same magnitude in the sample period.

4 Final Comments

This paper aimed to investigate the conditional volatility for growth in U.S. industrial production. The considered period includes a major negative shock in terms of the Civil War, and the possibility of asymmetric responses to economic shocks could not be ruled out beforehand. Taking as a reference the availability of improved historical time series for U.S. industrial production, as constructed by Davis (2004), it was possible to undertake a conditional volatility analysis that allowed for asymmetric effects. Although the sample spans a larger period, the discussion underscores the major negative shock provided by the Civil War. In fact, such a disruptive event could potentially favour asymmetric patterns for conditional growth volatility.

Upon the estimation of an EGARCH model, the obtained results suggest a persistent volatility but do not provide support for an asymmetric response to economic shocks. Ho and Tsui (2003) have also studied the U.S . economy, but for a later period (1961-1997) and with a modern series on GDP. The evidence also favours persistent conditional volatilities but shows asymmetric conditional volatilities. The referred authors also note that more significant growth volatility may require compensatory macroeconomic policies.[2].

It is worth noting the narrower scope of the industrial production index by Davis (2004) and the fact that stronger destruction of economic structures occurred in the South during the Civil War. Hence, asymmetric responses to shocks could be less pronounced or even absent, as suggested by the estimated results. Moreover, the aggregate industrial production index can potentially mask important asymmetries in several specific key sectors. For example, pig iron production could be especially important given its forward linkages, but the short series provided in Davis and Irwin (2008) precludes further econometric analysis.

Should the sectoral series be available, an interesting application would be to study conditional volatility at the sectoral level by means of multivariate models to obtain a disaggregated portrayal of growth volatility.

[2] Cecchetti et al. (2005) have discussed how economic policies can affect growth volatility in the context of more modern economies. In particular, the evidence indicates that the adoption of inflation-targeting mechanisms and increased central bank independence have been associated with less real growth volatility.

Appendix

The lag selections for the unit root tests were defined upon automatic procedures available in EVIEWS that involved the BIC in the case of ADF tests and a bandwidth automatic selection based in the Newey-West criterion in the case of the PP test.

Table A1
Unit Root Tests

Test	Test Statistic
ADF test (model with intercept)	-11.029*** (0)
Phillips-Perron test model with intercept)	-11.325*** (7)
ADF test (model with intercept and trend)	-10.991*** (0)
Phillips-Perron test model with intercept and trend)	-11.271*** (7)

Note: *** significant at the 1 % level, lags indicated in parentheses

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