E C O N O M I C S   B U L L E T I N

Macroeconomic and financial market volatilities: an empirical evidence of factor model

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Abstract

In this paper, we provide two empirical findings. First, exploring 140 monthly macroeconomic and financial variables and applying the principal components method, we find 12 static factors and 8 dynamic factors from 1959 to 2005 in the US. Second, we find the real factor and interest rate factor have been less volatile since the mid 1980s. The price factor and foreign exchange factor, in contrast, became more volatile in the late 1990s. The rest of the factors show no obvious pattern. We find that the real economy and financial market fluctuations are not closely related because they are driven by different factors.

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1. Introduction

The Great Moderation, which represents the substantial decline of volatilities of real output and inflation in the U.S. since the mid 1980s, has been well documented (Kim and Nelson 1999; MaConnell and Perez-Quiros 2000; Stock and Watson 2002a). As yet, there has been no widely accepted explanation for the main cause of the macroeconomic stability. Meanwhile, only few studies have proceeded on the impact of the Great Moderation on financial market activities. Are the real economy and financial market fluctuations related? Have less-volatile real activities resulted in the higher valuation and lower variation in the financial markets?

Lattau, Ludvigson, and Wachter (2008) suggested that the Great Moderation contributed to a lower long-run equity premium and lifted the stocks prices in the late 1990s. Campbell (2005) argued that the volatilities of investor's forecasts of future earnings, dividends and cash flow have declined substantially. In contrast, the volatility of the discount rate, which is the main force of stock market volatility, did not decline. Based on their habit formation model, Campbell and Cochrane (1999) showed that the volatility of investor's risk aversion is independent of macroeconomic volatility. Kim and Wright (2005) found that the large decline in long-term yields, distant-horizon forward rates, and term premiums since mid 2004 occurred because of the increased demand of long-term bonds coming from better anchored inflation expectations and a lower real variability.

In this paper, we use the factor model, which is based on principal component method, to analyze a large number of macroeconomic and financial series. The paper investigates the volatility of all financial markets, including the money, stocks, and bonds markets, rather than one specific market or financial indicator. The factor model presents the idea that the fluctuations and comovements of a large number of economic and financial variables are produced by a handful of observable or unobservable factors, which are driven by common structural shocks. Examples of observable factors in the literature include market return in the capital asset pricing model (CAPM), aggregate consumption in the consumption-based CCAPM models, common factors in the arbitrage pricing theory (APT), and the famous three factors in Fama and French's model. Fama and French's three factors are the market excess return, small minus big factor, and high minus low factor. Examples of unobservable/latent statistical factors in the literature include the three factors (level, slope, and curvature) of the term structure model by Nelson and Siegel (1987), dynamic factor models proposed by Sargent and Sims (1977), Geweke (1977), and Forni et al. (2000), and static factor models by Chamberlain and Rothschild (1983), Connor and Korajczyk (1986), and Stock and Watson (2002b, 2002c). Furthermore, modern dynamic general equilibrium macroeconomic models often assume that a small set of driving variables are responsible for the dynamics of macro time series.

This article finds 12 static factors and 8 dynamic factors using Bai and Ng's (2002, 2007) methods out of 140 macro and financial time series data sets from 1959:1 to 2005:11. The real factor has very different dynamics from the financial market factor. The former explains most of the variation of output, consumption, and employment, while the latter explains the fluctuations of a range of financial variables. In other words, we find that the real economy and financial market fluctuations are not closely related because they are driven by entirely different factors.

The rest of the paper is organized as follows. Section 2 applies the static factor model using principal component method to examine the factors. Section 3 concludes. Data resources and description are given in the Appendix.

2. Factor Model Analysis

In most of the literature, researchers only use a small number of variables to investigate the dynamics and relationship between macroeconomic and financial markets. Nevertheless, these limited variables are unlikely to span the information sets used by actual market participants and policy makers. For example, the Federal Reserve System and other central banks monitor and analyze a wide range of data series from different sources, frequencies, and levels of aggregation in preliminary and revised versions. Recent surveys confirm that professional forecasters, who use a large number of datasets, may significantly improve forecasts of key macroeconomic variables.

Nowadays, time series models and forecasting methods, however, only use a few series. For instance, vector autoregressions (VAR) typically contain fewer than 18 variables. Because some information is not reflected in this VAR analysis, it might not be enough to span the space of structural shocks and the measurement of policy shocks might be contaminated. A famous example is the “price puzzle.”[1] Furthermore, is the unemployment rate, capacity utilization, or real GDP the best measurement of the output gap in the Philips curve? Is any single real-time data of these variables reliable for forecasting and policy making? The factor model, which determines a few factors by a dimension reduction from the pooled information of all the candidate variables, offers an alternative method for modeling and forecasting. Stock and Watson (2002b, 2002c) considered forecasting real output and inflation with diffusion indexes constructed from a large number of time series data and found their forecasting method is superior to many other competing methods.

2.1. Static Factor Model

Consider the factor representation for multiple time series data X_t at a given *t*,

$$\underset{(N\times 1)}{X_t} = \underset{(N\times r)}{\Lambda}\underset{(r\times 1)}{F_t} + \underset{(N\times 1)}{e_t} \tag{1}$$

where $\Lambda = (\lambda_1, \lambda_2, \lambda_3, ...\lambda_N)'$ is the factor loadings, F_t is the static factor process, r is the number of static factors, and $e_t = (e_{1t}, e_{2t}, e_{3t}, ...e_{Nt})'$ is the idiosyncratic disturbance. The factor loadings, factor process, and idiosyncratic errors are not observable. In the classical model, it is assumed that $T > N$ and the disturbances are assumed to be *i.i.d.*, normally distributed and independent of the factor process. Normalizing the covariance matrix of *F* to be an identity matrix, the factor model covariance matrix is then

$$\Sigma = \Lambda\Lambda' + \Omega \tag{2}$$

where Ω is the diagonal covariance matrix of e_t. A root-*T* consistent and asymptotically normal estimator, $\hat{\Sigma} = (1/T)\sum_{t=1}^{T}(X_t - \bar{X})(X_t - \bar{X})'$ can be obtained, provided that Σ is non-singular. But the diagonal Ω assumption is unlikely to be appropriate in the macroeconomic model, because the variables are serially correlated and possibly cross-correlated. Following the approximate factor structure proposed by Chamberlain and Rothschild (1983) and Connor and Korajczyk (1986, 1988, 1993), we assume that e_{it} could be serially correlated. With large *N*, factors could be consistently estimated by the asymptotic principal component method.

[1] In low-dimensional VAR analysis, a contractionary monetary policy shock is followed by a rising price level in the impulse response functions instead of decreasing price that theory would suggest. The reason for this price puzzle is that it is the result of imperfectly controlling for information that the central bank may have for future inflation. When the policy response is only partially offset the inflation, the monetary tightening is followed by an increased price in mis-specified VAR. The price puzzle could be solved by including commodity price index as a signal of future inflation for central bank.

It is important to correctly specify the number of factors in factor models but the number is mostly assumed rather than estimated in the literature. In order to determine the number of factors by the data, Bai and Ng (2002) developed asymptotic results of consistent estimation of the number of factors when N and T are large. They started with an arbitrary number k ($k < \min\{N,T\}$). The number of static factors (r) is estimated by the information criteria (*IC*)

$$\hat{r} = \arg\min_{0 \le k \le k\max} \{\ln(\hat{\sigma}_k^2) + k(\frac{N+T}{NT})\ln C_{NT}^2\} \tag{3}$$

where $\hat{\sigma}_k^2 = (NT)^{-1}\sum_{i=1}^{N}\sum_{t=1}^{T}(X_{it} - \hat{\Lambda}^k \hat{F}^k)^2$, $\hat{F}^k$ is $k \times T$ and $C_{NT}^2 = \min\{N,T\}$.

2.2. Dynamic Factor Model

The static factor model considers the static relationship between X_{it} and F_t but r static factors could be dynamically related. The dynamic factor model is

$$X_{it} = \lambda(L) f_t + e_{it} \tag{4}$$

where $\lambda(L)$ with order s is a $N \times q$ matrix lag polynomial, called a dynamic factor loading. q is the number of dynamic factors, which also represents the number of primitive shocks. The dynamic factor model could be written as a static factor form (see Bai and Ng 2007). In (4), we assume that $\lambda_i(L)$ $= \lambda_{i0} + \lambda_{i1}L + ... + \lambda_{is}L^s$ and put it in the Λ of (1) where Λ_i is $[\lambda_{i0}, \lambda_{i1}, ..., \lambda_{is}]'$ and F_t = $[f_t, f_{t-1}, ..., f_{t-s}]'$. The dimension of F_t is r = q(s+1). If s = 0, it means r = q. If this is the case, there is no difference between the static and dynamic factors. Although little would be gained in forecasting from a distinction between the static and dynamic factors as long as N and $T \to \infty$ (Stock and Watson 2002c), it is important to understand the primitive shocks from the dynamic factor model.

Bai and Ng (2007) proposed an approach to estimate the number of dynamic factors. Given the known $\hat{r}$ from (3) estimated from the IC, we get $\hat{F}_t^r$ by using the principal component method. Let $\hat{u}_t$ be the residuals from estimating a VAR (p) in $\hat{F}_t^r$. The p is the lead and lag of the VAR process and $\hat{\Sigma}_u = (T)^{-1}\sum_{t=1}^{T}\hat{u}_t\hat{u}_t$. The number of dynamic factors could be determined from a spectral decomposition of $\hat{\Sigma}_u$ given T is large.

2.3. Data

The whole dataset used to estimate the factors contains 140 monthly time series in the U.S. from 1959:1 to 2005:11. Therefore, the N is 140 and T is 563 in our application. Bai (2003) developed an inferential theory for factor models of large dimensions. From their Monte Carlo simulation of N=100 and T=100, they got an average correlation coefficient of 0.9948 between estimated factors and true factors (p191). With N=100, the estimated factors could be a consistent measure of true factors. They also show that the confidence interval is narrow enough with N=100. Consequently, the estimation errors of factors in the paper would not be large. Following Stock and Watson (2002b, 2002c, 2005), the series were selected to represent broad categories of macroeconomic and financial time series - real output, income, consumption, employment, hours, construction, inventories, orders, money markets, interest rates, bond market, stock markets, exchange rate markets, and price indexes. The detailed description, sources and transformation of a complete list of series are given in the Appendix. Unlike Stock and Watson (2005), we have updated data with a little more weight on financial market indicators. We assume that X_{it} is I(0) so the series are subject to some stationary transformation: taking logarithms, first differencing, second differencing, or a combination of the above after preliminary data analysis and inspection. Basically, logarithms were taken for all nonnegative series that were not in percentage units. Most series were first differenced. Then the transformed data were further standardized to have zero mean and unit sample standard deviation.

2.4. Factors Interpretation

Using the principal component method (1) and following IC (5) from Bai and Ng (2002), we get 12 static factors. Based on Bai and Ng (2007) criteria for dynamic factors, we get 8 dynamic factors.[2] Table 1 presents the summary statistics of 12 estimated factors $\hat{F}_t$. From the accumulated R^2, the first 6 factors could explain 42 percent of the variation in the whole series and 12 factors could explain 56 percent of the variation. From marginal R^2, the first, second, third, fourth, and fifth factor explain 14.2, 7.8, 6, 4.9, and 4.6 percent of the variation respectively. To understand the persistence of the estimated static factors, we also calculate the AR(1) coefficient for each factor. All of the factors have a persistence parameter smaller than 0.77 but with widespread coefficients from 0.77 to -0.29.

Figure 1 shows the R^2 of the regressions of the 140 individual time series against each of the 12 factors. These R^2 are plotted as bar charts with one chart for each factor. The 140 series are grouped by category and ordered numerically based on the ordering in the Appendix. In general, Factor 1 loads heavily on output, consumption, employment, construction, and orders but is not correlated with price variables. This is a *real factor*, which is also the most important factor and accounts for 14.2 percent of the whole series. Factor 6, 7, and 10 also explain part of the variation of output, income, consumption, construction, inventories, and orders. They are also included among the real factors. Accordingly, we could see them as one dynamic factor. Figure 2(A) illustrates the correlation of the moving average of both industrial production growth and Factor 1. The graph confirms that the real factor explains most of the medium-run variation in industrial production.

Figure 3 plots the factor series and their time-varying volatility by GARCH(1,1). It is worth noting that Factor 6, which only contains the variation of output, construction and orders without accounting for any nominal movements, might be referred as the natural (potential) output fluctuated by the productivity shocks. In Figure 3(F), there is a downside slump of natural output from 1974 to 1977 and there is an upside trend since the early 1990s. Figure 2(B) also illustrates this possibility by comparing the 1-year moving average of Factor 6 and productivity growth computed from nonfarm business sector output per hour. Factor 2 accounts for most of the financial market variation, so we refer it as the *interest rate factor*. Factor 3 describes the most volatility in bond market, so it is called the *bond market factor*. Factor 4 accounts for most of the fluctuations of the commodity, producer and consumer price indexes, and we refer to it as the *price factor*. Factor 5 loads primarily on stock market and we call it as the *stock market factor*. Factor 8 explains mostly money market variation; it is named the *money market factor*. Factor 9 is the foreign exchange market since it captures mostly exchange rate market variation. Factor 11 and 12 are called *wage factors* because they load mainly wage movements.

From Figure 3(A), it is shown that Factor 1 (real factor) became stabilized since 1984 and we can see the similar pattern in Factor 2 (interest rate factor) from Figure 3(B). Therefore, the volatility of the aggregate financial market did get reduced because of Great Moderation. However, the bond market factor in Figure 3(C) and the stock market factor in Figure 3(E) did not become less volatile over the past two decades. There are two possible reasons. The first is that lightly regulated institutions such as investment banking companies, hedge funds and private equity are heavily involved in derivatives trading and leverage and are more and more influential in the financial market. The second is that emerging markets have been playing a bigger role in global financial markets since last decade. Meanwhile, the risks in emerging markets are naturally higher than those in the developed countries.

[2] Using different methods and similar range of data, Stock and Watson (2005) found 9 static factors and 7 dynamic factors. Using the same method but different range of data (1960:1-1998:12), Bai and Ng (2007) found 10 static factors and 7 dynamic factors.

The foreign exchange factor in Figure 3(I) has become destabilized since the mid 1990s. It may not be surprising that the price factor, composed of consumer, producer, and commodity prices indexes, has become more volatile since the late 1990s, in particular in the oil market for the past several years. If we view the price factor as cost-push shocks and Factor 6 as productivity shocks, since those two shocks did not become smaller or less frequent in the past two decades, the “good luck” hypothesis as the main explanation for Great Moderation suggested by Stock and Watson (2002a) might be more likely rejected. Finally, the better understanding of the dynamics of these factors would be helpful for policy makers to decide the potential/natural level of GDP and/or Non-Accelerating Inflation Rate of Unemployment (NAIRU).

3. Conclusions

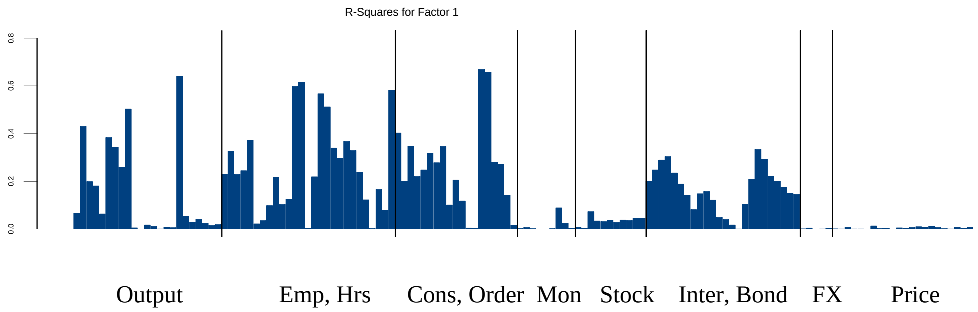
In this paper, we provide two empirical findings. First, exploring 140 monthly macroeconomic and financial variables and applying the principal component method, we find 12 static factors and 8 dynamic factors from 1959 to 2005 in the US. According to their properties and explanatory power, those factors are categorized and ordered as real factor, interest rate factor, bond market factor, price factor, stock market factor, money market factor, foreign exchange factor, and wage factor. Second, we find the real factor and interest rate factor have been less volatile since the mid 1980s. The price factor and foreign exchange factor, on the contrary, became more volatile in the late 1990s. The rest of the factors show no obvious pattern.

We find that the real economy and financial market fluctuations are not closely related because they are driven by different factors. Bai and Ng (2006) derived several tests that can serve as guides to tell which variables are close to the factors. They suggested the Fama and French factors are much better than any single macroeconomic variable to represent the factors in portfolios and individual stocks. Therefore, our findings are consistent with their conclusions about the dichotomy of macroeconomies and financial markets. In addition, the evidence from this paper sheds some light on the weakness of the “good luck” hypothesis as an explanation for the Great Moderation.

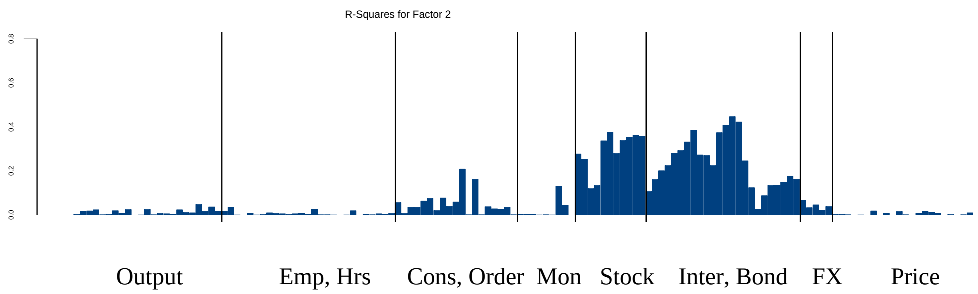
Table 1. Summary Statistics for Static Factors

Factor $\hat{F}_t$	Accumulated R^2	Marginal R^2	AR(1) coefficient	Description
1	0.142	0.142	0.774 (0.027)	Real factor
2	0.220	0.078	0.611 (0.033)	Interest rate factor
3	0.280	0.060	0.574 (0.035)	Bond market factor
4	0.329	0.049	-0.295 (0.040)	Price factor
5	0.375	0.046	0.418 (0.038)	Stock market factor
6	0.416	0.041	0.553 (0.035)	Real factor
7	0.447	0.031	0.584 (0.034)	Real factor
8	0.477	0.030	-0.080 (0.042)	Money market factor
9	0.500	0.023	0.282 (0.041)	Foreign exchange factor
10	0.523	0.023	0.140 (0.042)	Real factor
11	0.544	0.021	0.006 (0.042)	Wage factor
12	0.564	0.020	0.069 (0.042)	Wage factor

A. Marginal R-Squares for Factor 1: Real Factor



B. Marginal R-Squares for Factor 2: Interest Rate Factor



C. Marginal R-Squares for Factor 3: Bond Market Factor

D. Marginal R-Squares for Factor 4: Price Factor

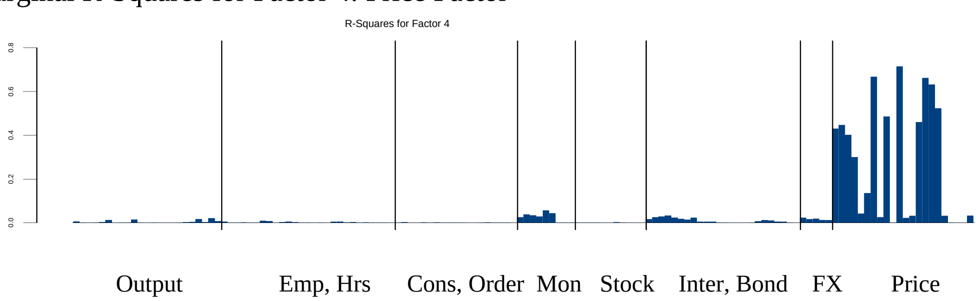
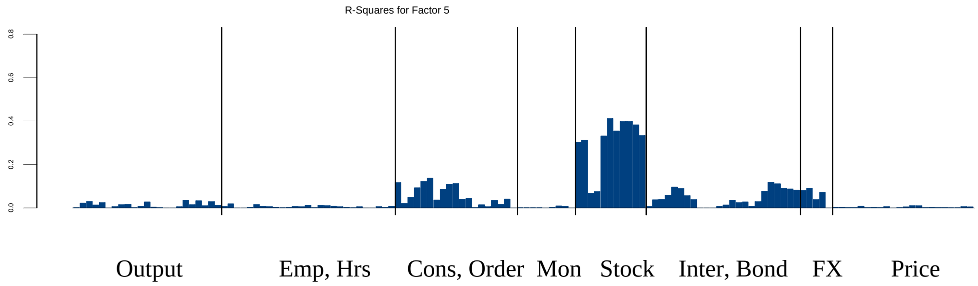
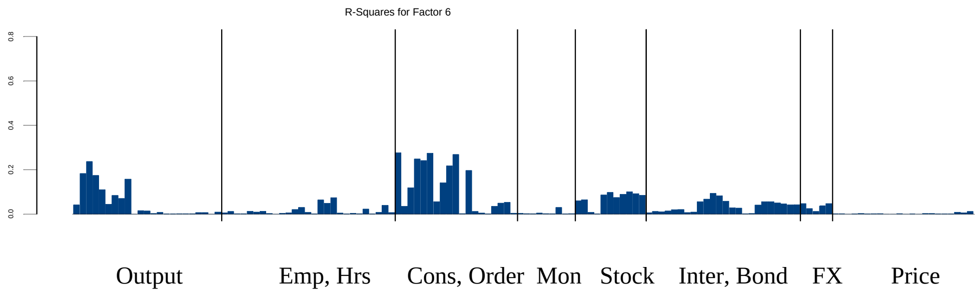


Figure 1. Marginal R-Squares for Factors

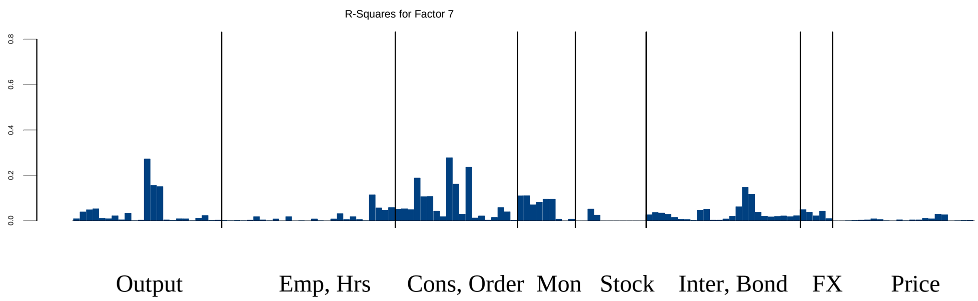
E. Marginal R-Squares for Factor 5: Stock Market Factor



F. Marginal R-Squares for Factor 6: Real Factor



G. Marginal R-Squares for Factor 7: Real Factor



H. Marginal R-Squares for Factor 8: Money Market Factor

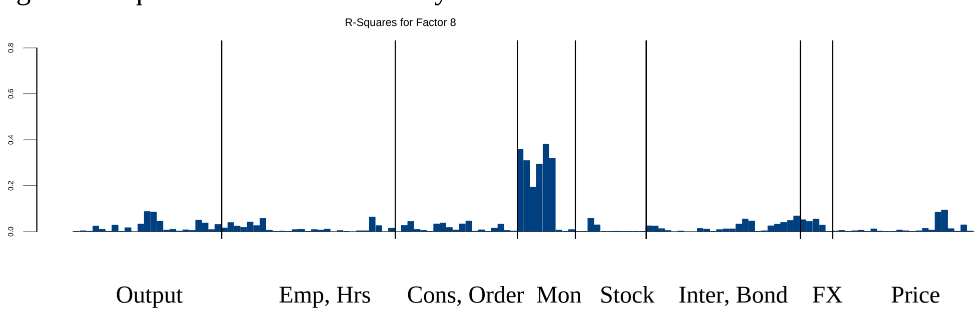
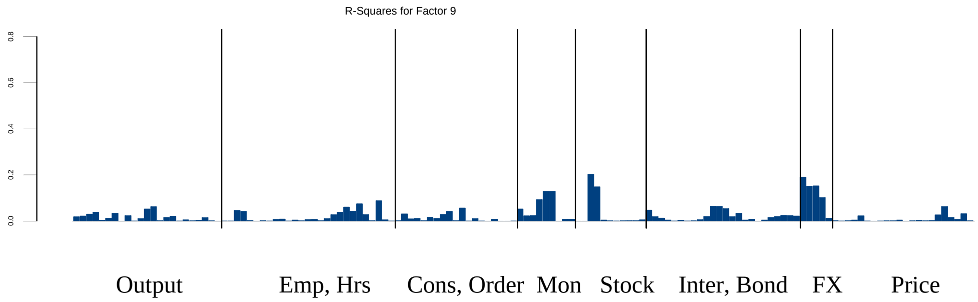
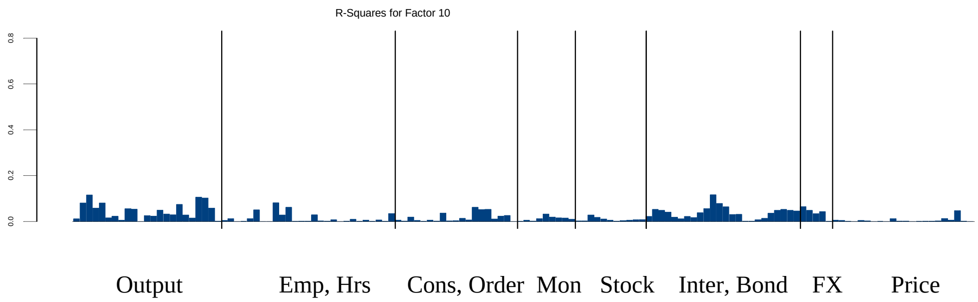


Figure 1. (Continued)

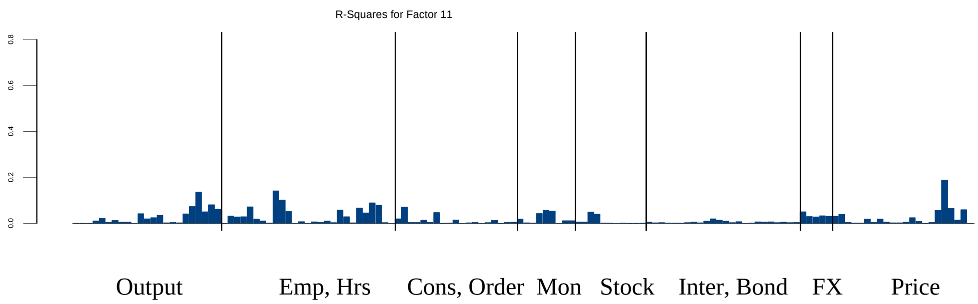
I. Marginal R-Squares for Factor 9: Foreign Exchange Factor



J. Marginal R-Squares for Factor 10: Real Factor



K. Marginal R-Squares for Factor 11: Wage Factor



L. Marginal R-Squares for Factor 12: Wage Factor

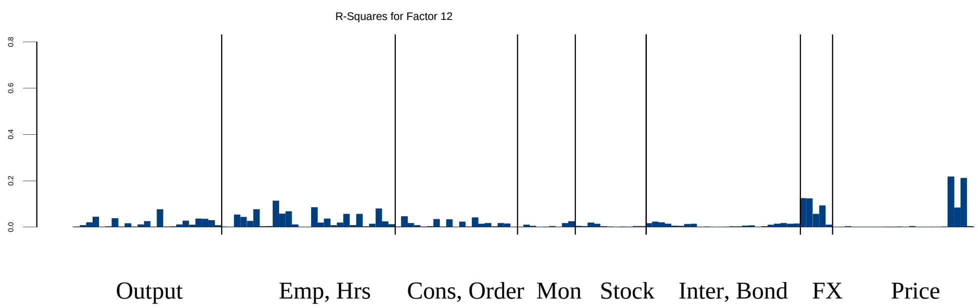


Figure 1. (Continued)

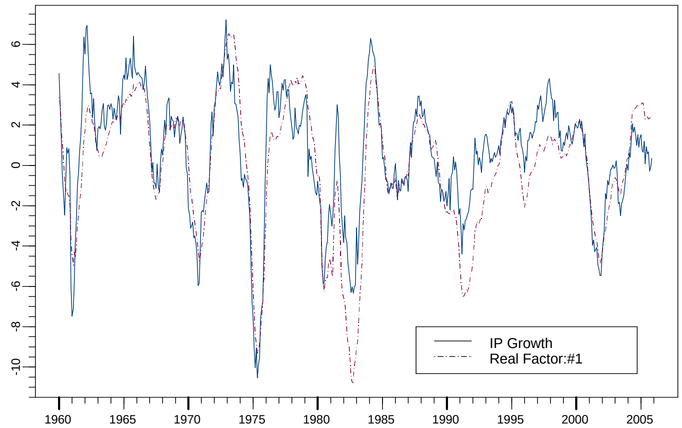


Figure 2A. Factor 1: Real Factor and IP Growth

Note: The plots are 12 months moving average of both IP growth and real factor.

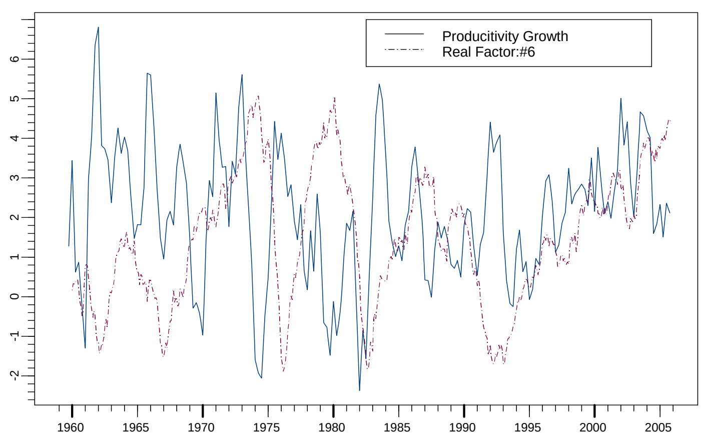
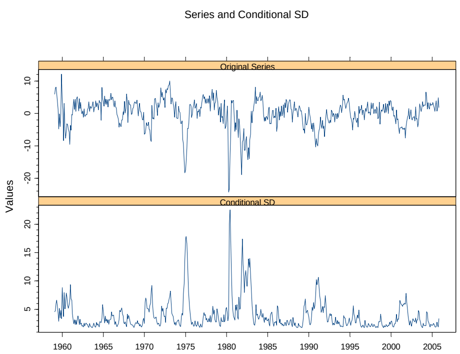


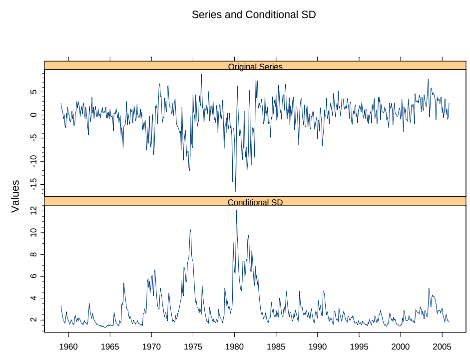
Figure 2B. Factor 6: Real Factor and Productivity Growth

Note: The plots are 12 months moving average of real factor and 4 quarters moving average of productivity growth measured by nonfarm business sector: output per hour

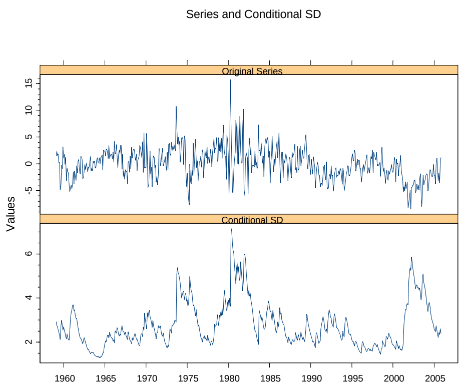
A. Factor 1: Real Factor



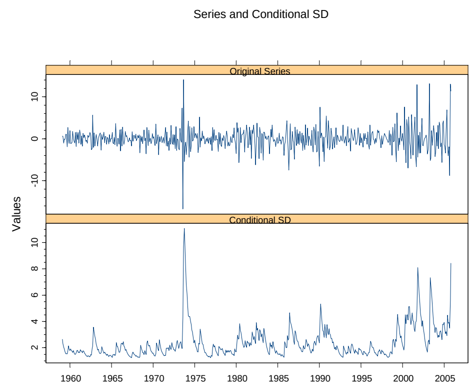
B. Factor 2: Interest Rate Factor



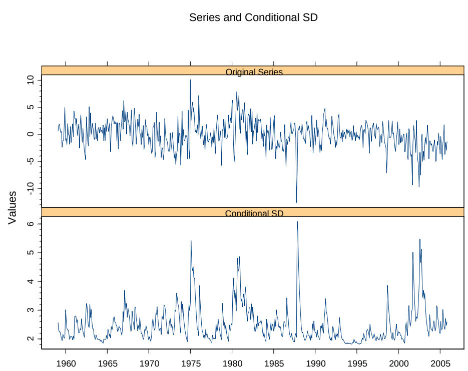
C. Factor 3: Bond Market Factor



D. Factor 4: Price Factor



E. Factor 5: Stock Market Factor



F. Factor 6: Real Factor

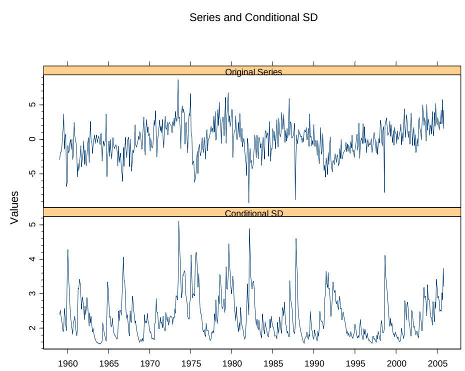
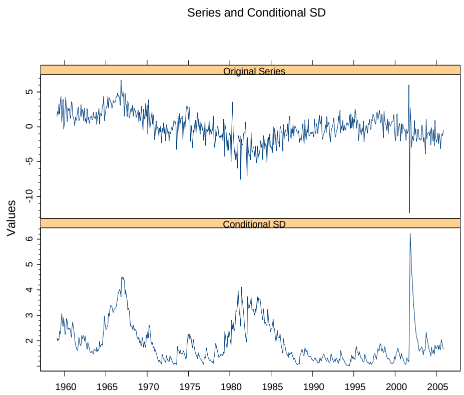
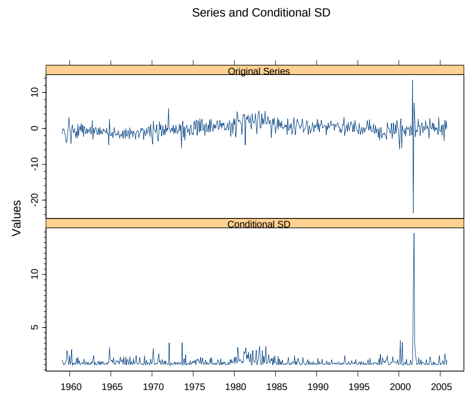


Figure 3. Factor Series and Its GARCH Volatility

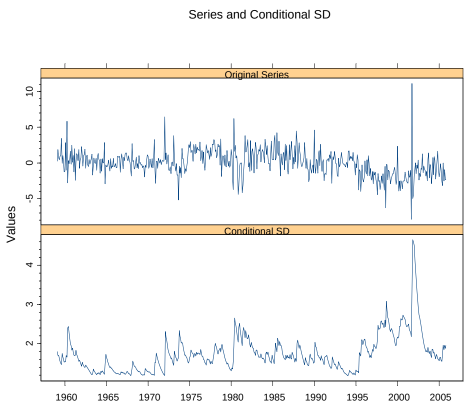
G. Factor 7: Real Factor



H. Factor 8: Money Market Factor



I. Factor 9: Foreign Exchange Factor



J. Factor 10: Real Factor

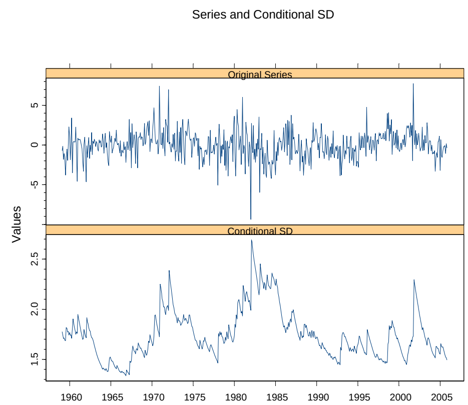


Figure 4. (Continued)

Appendix: Data Description

Table A lists the name, transformation, description, and sources of the data. In the transformation column, *lev* denotes the level of the series, *ln* denotes taking logarithms, *dlev* denotes the first difference of the series, *dln* denotes the first difference of the logarithm, *ddln* denotes the second difference of the series. All series are from DRI Basic Economics Database by Global Insights, Inc. unless the sources are listed in parentheses as FRED (Federal Reserve Economic Data from http://research.stlouisfed.org/FRED2/), CRSP (Center for Research in Security Prices) or AC (author's calculation from the based on the above data). And sa denotes seasonal adjustment saar denotes seasonal adjustment with annual rate.

Table A. Data transformation, description and sources

Number	Series	Trans.	Description
Real Output, Income, and Consumption			
1	ipn10	*dln*	industrial production index - total index
2	ips11	*dln*	industrial production index - products, total
3	ips12	*dln*	industrial production index - consumer goods
4	ips13	*dln*	industrial production index - durable consumer goods
5	ips18	*dln*	industrial production index - nondurable consumer goods
6	ips25	*dln*	industrial production index - business equipment
7	ips34	*dln*	industrial production index - durable goods materials
8	ips38	*dln*	industrial production index - nondurable goods materials
9	ips43	*dln*	industrial production index - manufacturing (sic)
10	ips306	*dln*	industrial production index - fuels
11	ips307	*dln*	industrial production index - residential utilities
12	cap11	*dln*	industrial capacity index - manufacturing
13	cap21	*dln*	industrial capacity index - motor vehicles and parts naics=3361-3
14	cap31	*dln*	industrial capacity index - petroleum and coal products naics=324
15	cap44	*dln*	industrial capacity index - primary & semifinished processing (capacity)
16	cap45	*dln*	industrial capacity index - finished processing (capacity)
17	pmp	*lev*	napm production index (percent)
18	pi	*dln*	personal income (FRED, saar)
19	dspic	*dln*	real disposable income (FRED, saar, chained 2000)
20	pcec	*dln*	personal consumption expenditures (FRED, saar, chained 2000)
21	Pcedgc	*dln*	personal consumption expenditures - durable goods (FRED, saar, chained 2000)
22	pcendc	*dln*	personal consumption expenditures - nondurable goods (FRED, saar, chained 2000)
23	pcesc	*dln*	personal consumption expenditures - services (FRED, saar, chained 2000)
Employment and Hours			
24	lhel	*dlev*	index of help-wanted advertising in newspapers (1967=100;sa)
25	lhelx	*dlev*	employment: ratio; help-wanted ads:no. unemployed clf
26	lhem	*dln*	civilian labor force: employed, total (thous.,sa)
27	lhnag	*dln*	civilian labor force:employed in nonag,both sexes 16-19yrs(thou.,
28	lhur	*dlev*	unemployment rate: all workers, 16 years & over (%,sa)

29	lhu680	*dlev*	unemploy.by duration: average(mean)duration in weeks (sa)
30	lhu5	*dln*	unemploy.by duration: persons unempl.less than 5 wks (thous.,sa)
31	lhu14	*dln*	unemploy.by duration: persons unempl.5 to 14 wks (thous.,sa)
32	lhu15	*dln*	unemploy.by duration: persons unempl.15 wks + (thous.,sa)
33	lhu26	*dln*	unemploy.by duration: persons unempl.15 to 26 wks (thous.,sa)
34	lhu27	*dln*	unemploy.by duration: persons unempl.27 wks + (thous,sa)
35	ces002	*dln*	employees on nofarm: total private
36	ces003	*dln*	employees on nonfarm: goods-producing
37	ces006	*dln*	employees on nonfarm: mining
38	ces011	*dln*	employees on nonfarm: construction
39	ces015	*dln*	employees on nonfarm: manufacturing
40	ces017	*dln*	employees on nonfarm: durable goods
41	ces033	*dln*	employees on nonfarm: nondurable goods
42	ces046	*dln*	employees on nonfarm: service-producing
43	ces048	*dln*	employees on nonfarm: trade, transportation, and utilities
44	ces049	*dln*	employees on nonfarm: wholesale trade
45	ces053	*dln*	employees on nonfarm: retail trade
46	ces088	*dln*	employees on nonfarm: financial activities
47	ces140	*dln*	employees on nonfarm: government
48	ces151	*lev*	avg wkly hours, prod wrkrs, nonfarm - goods-producing
49	ces155	*dlev*	avg wkly overtime hours, prod wrkrs, nonfarm - mfg
50	pmemp	*lev*	napm employment index (percent)

Construction, Inventories and Orders

51	hsfr	*ln*	housing starts:nonfarm(1947-58);total farm&nonfarm(1959-)(thous.,sa
52	hsne	*ln*	housing starts:northeast (thous.u.)s.a.
53	hsmw	*ln*	housing starts:midwest(thous.u.)s.a.
54	hssou	*ln*	one-family houses sold:south(thou.u.,s.a.)
55	hswst	*ln*	housing starts:west (thous.u.)s.a.
56	hsbr	*ln*	housing authorized: total new priv housing units (thous.,saar)
57	hsbne	*ln*	houses authorized by build. permits:northeast(thou.u.)s.a
58	hsbmw	*ln*	houses authorized by build. permits:midwest(thou.u.)s.a.
59	hsbsou	*ln*	houses authorized by build. permits:south(thou.u.)s.a.
60	hsbwst	*ln*	houses authorized by build. permits:west(thou.u.)s.a.
61	hnr	*ln*	new 1-family houses, month's supply @ current sales rate(ratio)
62	hniv	*ln*	new 1-family houses for sale at end of month (thous,sa)
63	ivm	*dln*	inventories - all manufacturing industries naics (m3)
64	pmi	*lev*	purchasing managers' index (sa)
65	pmno	*lev*	napm new orders index (percent)
66	pmdel	*lev*	napm vendor deliveries index (percent)
67	pmnv	*lev*	napm inventories index (percent)
68	mocmq	*dln*	new orders (net) - consumer goods & materials, 1996 dollars (bci)
69	msondq	*dln*	new orders, nondefense capital goods, in 1996 dollars (bci)

Money, Credit, and Finance

Money Market

70	fm1	*ddln*	money stock: m1(curr,trav.cks,dem dep,other ck'able dep)(bil$,sa)
71	fm2	*ddln*	money stock:m2(m1+o'nite rps,euro$,g/p&b/d mmmfs&sav&sm time dep(bil$,

72	fm3	*ddln*	money stock: m3(m2+lg time dep,term rp's&inst only mmmfs)(bil$,sa)
73	fmfba	*ddln*	monetary base, adj for reserve requirement changes(mil$,sa)
74	fmrra	*ddln*	depository inst reserves:total,adj for reserve req chgs(mil$,sa)
75	fmrnba	*ddln*	depository inst reserves:nonborrowed,adj res req chgs(mil$,sa)
76	busloans	*dln*	commercial and industrial loans at all commercial banks (FRED, sa)
77	fclbmc	*lev*	wkly rp lg com'l banks:net change com'l & indus loans(bil$,saar)
78	ccinrv	*ddln*	consumer credit outstanding - nonrevolving(g19)

Stock Market

79	fspcom	*dln*	s&p's common stock price index: composite (1941-43=10)
80	fspin	*dln*	s&p's common stock price index: industrials (1941-43=10)
81	fsdxp	*lev*	s&p's composite common stock: dividend yield (% per annum)
82	fspxe	*lev*	s&p's composite common stock: price-earnings ratio (%,nsa)
83	vwindd	*dln*	nyse value-weighted market index, excluding dividends (CRSP)
84	ewindd	*dln*	nyse equal-weighted market index, excluding dividends (CRSP)
85	nyca1	*dln*	nyse cap 1 market index (CRSP)
86	nyca2	*dln*	nyse cap 3 market index (CRSP)
87	nyca3	*dln*	nyse cap 5 market index (CRSP)
88	nyca4	*dln*	nyse cap 7 market index (CRSP)
89	nyca5	*dln*	nyse cap 9 market index (CRSP)

Interest Rate and Bond Market

90	fyff	*dlev*	interest rate: federal funds (effective) (% per annum,nsa)
91	fygm3	*dlev*	interest rate: u.s.treasury bills,sec mkt,3-mo.(% per ann,nsa)
92	fygm6	*dlev*	interest rate: u.s.treasury bills,sec mkt,6-mo.(% per ann,nsa)
93	fygt1	*dlev*	interest rate: u.s.treasury const maturities,1-yr.(% per ann,nsa)
94	fygt5	*dlev*	interest rate: u.s.treasury const maturities,5-yr.(% per ann,nsa)
95	fygt10	*dlev*	interest rate: u.s.treasury const maturities,10-yr.(% per ann,nsa)
96	fyaaac	*dlev*	bond yield: moody's aaa corporate (% per annum)
97	fybaac	*dlev*	bond yield: moody's baa corporate (% per annum)
98	sfygm3	*lev*	fygm3-fyff (AC)
99	sfygm6	*lev*	fygm6-fyff (AC)
100	sfygt1	*lev*	fygt1-fyff (AC)
101	sfygt5	*lev*	fygt5-fyff (AC)
102	sfygt10	*lev*	fygt10-fyff (AC)
103	sfyaaa	*lev*	fyaaac-fyff (AC)
104	sfybaa	*lev*	fybaaac-fyff (AC)
105	t30ret	*lev*	u.s.treasury bills 30 days return (CRSP)
106	t90ret	*lev*	u.s.treasury bills 90 days return (CRSP)
107	b1ret	*lev*	u.s.treasury bond I year return (CRSP)
108	b2ret	*lev*	u.s.treasury bond 2 year return (CRSP)
109	b5ret	*lev*	u.s.treasury bond 5 year return (CRSP)
110	b7ret	*lev*	u.s.treasury bond 7 year return (CRSP)
111	b10ret	*lev*	u.s.treasury bond I0 year return (CRSP)
112	b20ret	*lev*	u.s.treasury bond 20 year return (CRSP)
113	b30ret	*lev*	u.s.treasury bond 30 year return (CRSP)

Exchange Rate Market

114	exrus	*dln*	united states;effective exchange rate(merm)(index no.)
115	exrsw	*dln*	foreign exchange rate: switzerland (swiss franc per u.s.$)

116	exrjan	*dln*	foreign exchange rate: japan (yen per u.s.$)
117	exruk	*dln*	foreign exchange rate: united kingdom (cents per pound)
118	exrcan	*dln*	foreign exchange rate: canada (canadian $ per u.s.$)

Price and Wage Indexes

119	pwfsa	*ddln*	producer price index: finished goods (82=100,sa)
120	pwfcsa	*ddln*	producer price index:finished consumer goods (82=100,sa)
121	pwimsa	*ddln*	producer price index:intermed mat.supplies & components(82=100,sa)
122	pwcmsa	*ddln*	producer price index:crude materials (82=100,sa)
123	psccom	*ddln*	spot market price index:bls & crb: all commodities(1967=100)
124	pmcp	*ddln*	napm commodity prices index (percent)
125	punew	*ddln*	cpi-u: all items (82-84=100,sa)
126	pu83	*ddln*	cpi-u: apparel & upkeep (82-84=100,sa)
127	pu84	*ddln*	cpi-u: transportation (82-84=100,sa)
128	pu85	*ddln*	cpi-u: medical care (82-84=100,sa)
129	puc	*ddln*	cpi-u: commodities (82-84=100,sa)
130	pucd	*ddln*	cpi-u: durables (82-84=100,sa)
131	pus	*ddln*	cpi-u: services (82-84=100,sa)
132	puxf	*ddln*	cpi-u: all items less food (82-84=100,sa)
133	puxhs	*ddln*	cpi-u: all items less shelter (82-84=100,sa)
134	puxm	*ddln*	cpi-u: all items less midical care (82-84=100,sa)
135	pcepi	*ddln*	personal consumption expenditures: chain-type price index (FRED, sa)
136	pcepilfe	*ddln*	pce: chain-type price index less food and energy (FRED, sa)
137	ces275	*ddln*	avg hrly earnings, prod wrkrs, nonfarm - goods-producing
138	ces277	*ddln*	avg hrly earnings, prod wrkrs, nonfarm - construction
139	ces278	*ddln*	avg hrly earnings, prod wrkrs, nonfarm - mfg
140	hhsntn	*lev*	u. of mich. index of consumer expectations(bcd-83)

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