A two-year revision: cross comparison and modeling of Goldman Sachs, Morgan Stanley, JPMorgan Chase, Bank of America, and Franklin Resources

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Abstract

Approximately two years ago we presented results of price modeling and extensive statistical analysis for share prices of five banks: Bank of America (BAC), Franklin Resources (BEN), Goldman Sachs (GS), JPMorgan Chase (JPM), and Morgan Stanley (MS). Using monthly closing prices (adjusted for splits and dividends) as a proxy to stock prices, we estimated the best fit (*LSQ*) quantitative price models based on the decomposition into two defining consumer price indices selected from a large set of various consumer price indices (CPIs). It was found that there are two pairs of similar price models BAC/MS and GS/JPM, with a standalone model for BEN. Using five estimated models we formulated a procedure for selection the company with the highest return depending on the future evolution of defining CPIs. Here, we revisit the original models with new data for the period between October 2012 and February 2014. All revised models are practically the same as the original ones that validates our approach to price modeling. For the pair Bank of America and Morgan Stanley, we correctly predicted that both prices would rise synchronously (the observed return since October 2012 is approximately 75%) as driven by a higher rate of increase in the price index of owner's rent of primary residence and rent of shelter. Goldman Sachs and JPMorgan Chase have risen by ~40% in line with a higher rate of growth in the index of food and beverages relative to two rent related indices. Franklin Resources has risen by only 25% as defined by a different pair of CPIs. All five models are robust and do not demonstrate any signs of upcoming failure in the near future. They may be used for stock market analysis.

Key words: E4, G1, G2, G3
JEL Classification: share price, modeling, CPI, prediction, USA, bankruptcy

Introduction

Five years ago we presented an extended set of share price models for oil companies as based on the evolution of consumer price indices (Kitov, 2009). For a few financial companies from the S&P 500 list, we studied the probability of bankruptcy during the 2008/2009 period and built a number of quantitative models including those for Goldman Sachs (NYSE: GS), Morgan Stanley (MS), JPMorgan Chase (JPM), Bank of America (BAC), and Franklin Resources (BEN) (Kitov, 2010). We have been following the evolution of these five stock prices and their respective models since 2010 and found a lengthy period characterized by unchanged models.

Our deterministic model for the evolution of stock prices implies "mechanical" the dependence on consumer prices of various goods and services (Kitov, 2010). The term "mechanical" has multiple meanings. Firstly, it expresses mechanistic character of the link when any change in the price defining CPIs is one-to-one converted into the change in the stock prices, as one would expect in a system of blocks and leverages. Secondly, this deterministic link does not depend on human beings in sense of their rational or irrational behavior or expectations. In its ultimate form, the macroeconomic concept behind the stock price model relates the market prices to populations or the numbers of people in various age groups. Accordingly, the populations consist of the simplest possible objects; only their numbers matter. Thirdly, this link is a linear one, as in classical mechanics reaction is proportional to the size of proactive change. In all these regards, we consider our pricing model as mechanical, and thus, it is a physical one rather than an economic or financial. Essentially, we work with measured numbers not with the piles of information behind any stock.

Having five different banks it was instructive to carry out a quantitative comparison of their models. Two years ago, our goal was to reveal similarities and differences between the models and thus between the companies (Kitov, 2012). When two or more companies are driven by similar forces (same CPIs in our model) it is always helpful to understand which of the companies provides larger returns. Companies with not correlating price histories driven by different forces may be a natural choice to diversify a defensive portfolio. This article revises the results of the 2012 study with new data for the period between October 2012 and February 2014.

Following the previously developed procedure, we characterize five time series statistically. Cross correlation coefficients are estimated for all pairs of stock price series. Then we model five time series with new data and demonstrate that the original pricing models are reliable. As before, we successfully test the predicted and observed prices for cointegration. Finally, we compare the pricing models and discuss their similarity and difference in terms of investment opportunities and ideas.

1. Statistical estimates

Figure 1 displays the monthly closing (adjusted for splits and dividends) prices for five financial companies for the period between July 2003 and February 2014. Notice that GS price is divided by 10 in order to shrink the price scale. All curves have peaks in 2007 and troughs in 2009. There are significant differences, however. JPM and BEN have grown above their peak pre-crisis levels (approximately by 30%) with the other three companies demonstrating lower performance: 0.35 of the peak value for BAC, 0.48 for MS, and 0.72 for GS.

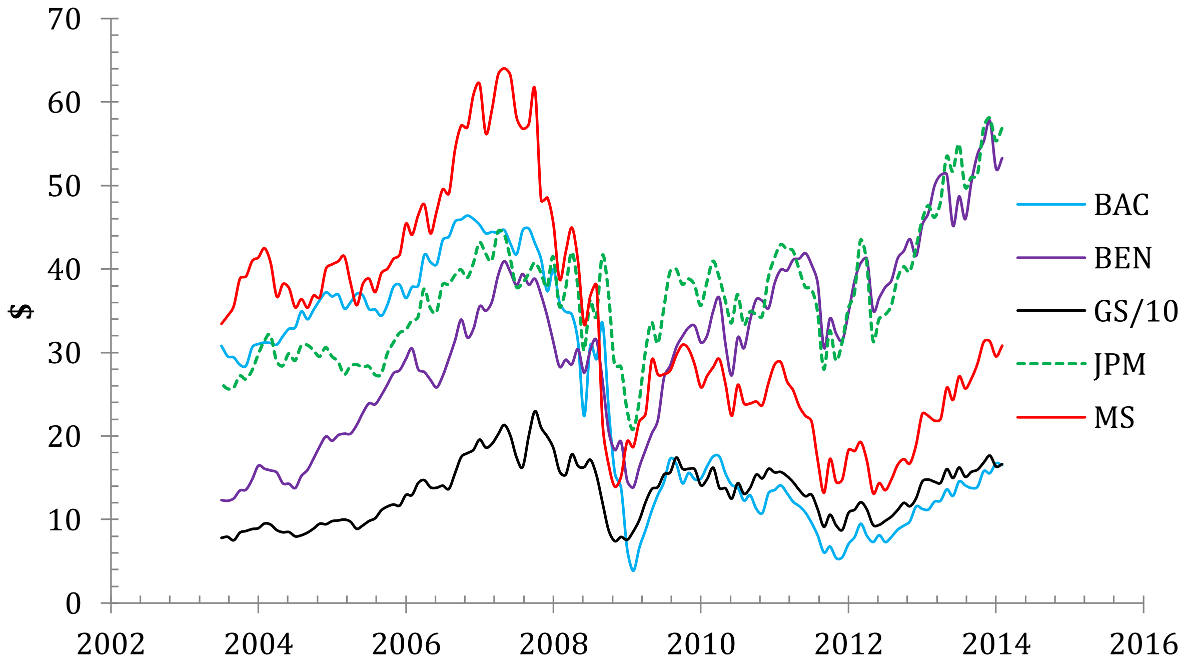


Figure 1. The evolution of JPM, MS, GS, BAC, and BEN share prices. The GS price is divided by 10 in order to shrink the price scale.

Table 1 lists the cross correlation coefficients for all pairs of five time series. All series span the interval between July 2003 and February 2014, which includes 128 monthly readings. In brackets, we list the cross correlation coefficients obtained in October 2012. There is no dramatic change in these coefficients since 2012, with deviations in both directions. There are highly correlated series and not correlating ones. Not surprisingly, the cross correlation coefficient between BAC and MS, which both have been suffering most after 2007, is 0.92. At the same time, BAC share price series does not correlate with the series from other three banks. Franklin Resources correlate with Goldman Sachs and JPMorgan Chase, with the cross correlation coefficient between the latter two companies of 0.7 (0.8 in 2012). Higher cross correlation coefficients suggest that driving forces behind the relevant time series are likely similar.

Table 1. Cross correlation coefficients for five time series of monthly closing prices. Diagonal elements (highlighted red) are the coefficients of determination, R^2, as estimated from a linear regression of actual and predicted time series for a given company.

	BAC	BEN	GS	JPM	MS
BAC	0.95 (0.95)				
BEN	-0.33 (-0.19)	0.95 (0.93)			
GS	0.24 (0.31)	0.62 (0.66)	0.84 (0.86)		
JPM	-0.14 (0.10)	0.88 (0.81)	0.69 (0.80)	0.81 (0.72)	
MS	0.92 (0.92)	-0.15 (-0.01)	0.48 (0.55)	0.03 (0.26)	0.93

In Table 1, we also present simple statistical estimates of the model reliability, which will be discussed later on. Diagonal elements (highlighted red) are the coefficients of determination, R^2, as estimated by linear regression of actual and predicted time series for a given company. The estimated values are high and demonstrate that all models are reliable in statistical terms. The highest R^2=0.95 is estimated for the BAC model and the lowermost R^2=0.81 is obtained for JPMorgan Chase. It is interesting that the correlation coefficient for BEN/JPM pair has grown because these companied have similar rallies since 2012. All involved series of monthly share prices are likely non-stationary processes. We have carried out several unit root tests (the augmented Dickey-Fuller and Phillips-Perron), which showed that they are all I(1) processes. This means that cross correlation coefficients in Table 1 are subject to a positive bias.

Figure 2 presents the evolution of five share prices since October 2012. Bank of America and Morgan Stanley have grown synchronously by approximately 75%; both are driven by a higher rate of increase in the price index of owner's equivalent rent of residence and rent of shelter (Kitov, 2012). Stocks of Goldman Sachs and JPMorgan Chase have risen by ~40%. Franklin Resources, who is the leader of growth since 2009, has risen by only 25% from October 2012. This segment of price evolution is a challenge for any quantitative modeling – after two troughs in 2008/2009 and 2011/2012 is it difficult to predict the current rally. For investors, it is important to know the length of this rally and the level reached by each company at the end of the rally.

1. Quantitative model

The concept of share pricing based on the link between consumer and stock prices has been under development since 2008 (Kitov, 2009). In the very beginning, we found a statistically reliable relationship between ConocoPhillips' stock price and the difference between the core and headline consumer price index (CPI) in the United States. In order to increase the accuracy and reliability of the quantitative model we extended the set of defining CPIs to 92, which includes all major categories like food, housing, transportation etc. and many smaller subcategories. In this set, there are CPIs with similar time series, e.g. the price index of food and beverages, *F*, and the index of food only, *FB* (Kitov, 2010). We tested the model for stability relative to these highly correlated time series.

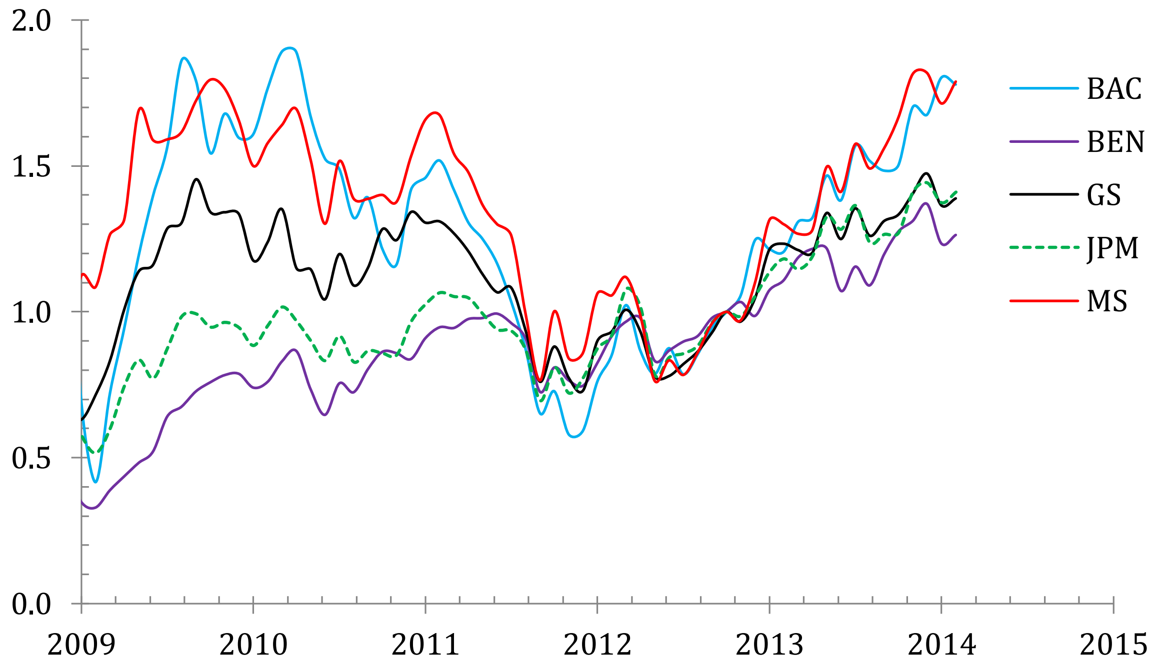


Figure 2. The evolution of JPM, MS, GS, BAC, and BEN share prices, all normalized to their respective values in October 2012.

With the extended set of defining CPIs, we estimated quantitative models for all companies from the S&P 500. A few additional companies with traded stocks were also estimated. Our model describes the evolution of a share price as a weighted sum of two individual consumer price indices selected from the set of CPIs. We allow only two defining CPIs, which may lead the modelled share price or lag behind it by several months. The intuition behind these positive and negative lags is that some companies are price setters and some are price takers. The former should influence the relevant CPIs, which include goods and services these companies produce. The latter companies lag behind the prices of goods and services they are associated with. In order to calibrate the model relative to the starting levels of the involved indices and to compensate sustainable time trends (Kitov and Kitov, 2008) (some indices are subject to secular rise or fall) we introduced a linear time trend and constant term. In its general form, the pricing model is as follows:

$$p(t_j) = \Sigma b_i \cdot CPI_i(t_j\text{-}\tau_i) + c \cdot (t_j\text{-}2000\ ) + d + e_j \qquad (1)$$

where $p(t_j)$ is the share price at discrete (calendar) times t_j, j=1,…,J; $CPI_i(t_j\text{-}\tau_i)$ is the i-th component of the CPI with the time lag τ_i, i=1,..,I (I=2 in all our models); b_i, c and d are empirical coefficients of the linear and constant term; e_j is the residual error, whose statistical properties have to be scrutinized. Without loss of generality, we model the monthly closing prices adjusted for splits and dividends. The monthly rate is related to the rate of CPI estimates – the frequency of output should not be larger than the frequency of input. One may use the high/low monthly prices as well as the monthly average price. We tried the monthly average of the daily closing prices and found the same models with slightly different coefficients.

By definition, the bets-fit model minimizes the RMS residual error. (One may introduce various metrics to define the best fit.) It is a fundamental feature of the model that the lags may be both negative and positive. In this study, we limit the largest lag (lead) to eleven (eight) months. System (1) contains J equations for $I+2$ coefficients. We start our model in July 2003 and the share price time series has 128 readings in study. To resolve the system, standard methods of matrix inversion are used.

Since October 2012 we have 16 new CPI estimates together with monthly closing prices. We first estimate the model with contemporary (February 2014) readings of stock price and CPIs, with all possible CPI pairs tested with (1). Then we allow both CPIs lead (to be earlier in time) the price by one and more (but less than 12) months and also estimate all possible pairs of CPI with all possible (negative) lags. For February 2014, the best fit model has to have the smallest standard error among all estimated models.

In order to ensure that the same model was the best during a longer period we carry out a similar estimate for January 2014 and then, one-by-one, for six previous months. There is a difference for these earlier models. For January 2014, one has future CPIs estimates for February 2014 (etc.) and these CPIs may lag behind the price change from one (January 2014 model) to seven (August 2013 model) months. Thus, we have to test all models with the CPIs lagging behind the price, which can have lower standard errors. When the best fit model for January is the same as for February, i.e. defined by the same CPIs with similar lags and coefficients in (1), we consider this observation as an indication of the model reliability.

For a closing price in December 2013, the defining CPIs for February 2014 lag by two months and we have more models to test, with lagging and leading CPIs. Overall, a model is considered as a reliable one when the defining CPIs are the same during seven months in a row. The largest lag and the diversity of CPI subcategories are both crucial parameters. It is possible to extend the set of defining CPIs and the length of model reliability. Regular revisions to all models are important to guarantee the long-term reliability. This paper extends the period of reliability by 16 months.

Why do we rely on consumer price indices in our modeling? Many readers may have reasonable doubts that some consumer price, which is not directly related to goods and services produced by a given company, may affect its price. We allow the economy to be a more complex system than described by a number of simple linear relations between share prices and goods. The connection between a firm and its products may be better expressed by goods and services which the company does not produce. The demand/supply balance is not well understood yet and may evolve along many nonlinear paths with positive and negative feedbacks. It would be too simplistic to directly define a company price by its products.

So, the intuition behind our pricing model is likely more insightful - we link a given share to some goods and services (and thus their consumer price indices), which we have to find among various CPIs. In order to provide a dynamic reference we also introduce in the model some relative and independent level of prices (also expressed by CPIs). Hence, one needs two different CPIs to define a share price model. These CPIs we select from a predetermined set of 92 CPIs by minimizing the residual model error. All in all, we assume that any share price can be represented as a weighted sum of two consumer price indices (not seasonally adjusted in our model) which may lead the modeled share price by several months. Our model also includes a linear time trend and an intercept in order to remove mean and trend components from all involved time series.

2. Modeling results

As two years ago, we begin with a report on the defining parameters for Goldman Sachs for the period between August 2013 and February 2014. Table 2 updates the previously reported list of the best fit models with seven months. Instructively, all fifteen models are based on the same defining CPIs – the consumer price index of food and beverages, *F*, and the index of owners' equivalent rent of residence, *ORPR*. In all cases, the lags are the same: three and two months, respectively. Other coefficients and the standard error suffer just slight oscillations or drifts (e.g. c and d). It is important to stress again that all models, except those for October 2012 and February 2014, may include some future CPIs. Table 2 confirms that no future CPIs drive this share price since March 2012. Goldman Sachs can be considered as a price setter. We have obtained the following best fit model for GS:

$$GS(t) = -13.795F(t\text{-}3) + 11.027ORPR(t\text{-}2) + 29.935(t\text{-}2000) + 33.751,\ \text{October 2012}$$
$$GS(t) = -13.038F(t\text{-}3) + 10.556ORPR(t\text{-}2) + 27.62(t\text{-}2000) + 12.86,\ \text{February 2014} \qquad (2)$$

Table 2. The monthly models for GS for eight months in 2012 and for seven months in 2014/2013.

Month	C_1	t_1	b_1	C_2	t_2	b_2	c	d	sterr,$
				2012					
October	*F*	3	-13.795	*ORPR*	2	11.027	29.935	33.751	14.521
September	*F*	3	-13.791	*ORPR*	2	11.013	29.992	35.827	14.584
August	*F*	3	-13.787	*ORPR*	2	11.003	30.023	37.106	14.649
July	*F*	3	-13.759	*ORPR*	2	10.978	30.018	37.647	14.707
June	*F*	3	-13.731	*ORPR*	2	10.933	30.124	41.985	14.758
May	*F*	3	-13.704	*ORPR*	2	10.876	30.342	48.755	14.770
April	*F*	3	-13.661	*ORPR*	2	10.819	30.449	53.171	14.805
March	*F*	3	-13.787	*ORPR*	2	10.943	30.440	48.639	15.055
				2014	**and**	**2013**			
February	*F*	3	-13.038	*ORPR*	2	10.556	27.62	12.86	14.25
January	*F*	3	-13.3166	*ORPR*	2	10.660	28.88	34.69	14.02
December	*F*	3	-13.4606	*ORPR*	2	10.687	29.71	51.36	13.91
November	*F*	3	-13.4537	*ORPR*	2	10.676	29.75	52.34	13.96
October	*F*	3	-13.5352	*ORPR*	2	10.700	30.13	60.04	14.00
September	*F*	3	-13.5638	*ORPR*	2	10.683	30.44	67.71	14.03
August	*F*	3	-13.6031	*ORPR*	2	10.691	30.66	72.06	14.07

In Tables 3 through 6, we summarize the evolution of models for four banks and two studied periods. Taking the defining CPIs and coefficients for February 2014 one obtains the following best fit models:

$$BAC(t) = -5.77SEFV(t\text{-}0) + 2.61RSH(t\text{-}2) + 19.99(t\text{-}2000) + 435.05, \qquad (3)$$
$$MS(t) = -7.57SEFV(t\text{-}0) + 4.26ORPR(t\text{-}2) + 23.66(t\text{-}2000) + 398.90, \qquad (4)$$
$$JPM(t) = -5.02SEVF(t\text{-}0) + 2.46RPR(t\text{-}3) + 17.89(t\text{-}2000) + 373.10, \qquad (5)$$
$$BEN(t) = -2.38FB(t\text{-}4) - 0.50O(t\text{-}9) + 22.75(t\text{-}2000) + 504.08, \qquad (6)$$

where *SEFV* is the consumer price index of food away from home, *RSH* is the index of rent of shelter, *FB* is the index of food without beverages, *RPR* is the index of rent of primary residence, and *O* is the index of other goods and services. All five models include indices related to food. Figure 3, where all the CPIs curves are depicted, shows that *FB* and *F* are practically identical and we might exclude one of them from the full set of CPIs without any significant loss in resolution. On the other hand, the BEN model is stable with *FB* since March 2012 and we retain it in the set. The model for JPM has changed from *F* to *SEVF* and from *ORPR* to *RPR*, which is not a big change as Figure 3 implies.

In four from five models, the second CPI is associated with rent of residence (*OPPR, RPR*) or shelter (*RSH*). Figure 3 demonstrates that these indices are also close. Table 7 lists cross correlation coefficients, *CC*, for seven defining CPIs and their first differences. Because of secular growth in prices, these coefficients are extremely high for the original series, but these *CC* values are likely biased up. The first differences characterize the link between indices in a more reliable way, with *CC*=0.994 for the first differences of *F* and *FB*. The first difference of *SEFV*, *dSEFV*, is well correlated with d*F* and d*FB*. Taking into account all possible time lags between the indices (from 0 to 11 months) in the models one may calculate cross correlation coefficients for the same time series but with various time shifts. Obviously, the highest cross correlation coefficients should not be lower than that for the contemporary time series. Overall, it is possible to distinguish three different sets of CPIs: “food”, “rent”, and “other”.

Table 3. The models for BAC. The last column lists standard errors.

Month	C_1	t_1	b_1	C_2	t_2	b_2	*c*	*d*	**sterr,$**
				2012					
October	*SEFV*	0	-5.897	*RSH*	2	2.650	20.609	444.030	2.983
September	*SEFV*	0	-5.906	*RSH*	2	2.656	20.625	444.228	2.979
August	*SEFV*	0	-5.965	*RSH*	2	2.679	20.868	448.932	2.962
July	*SEFV*	0	-5.953	*RSH*	2	2.684	20.751	446.137	2.953
June	*SEFV*	0	-5.989	*RSH*	2	2.695	20.924	449.647	2.952
May	*SEFV*	0	-5.982	*RSH*	2	2.699	20.850	447.823	2.949
April	*SEFV*	0	-5.960	*RSH*	2	2.690	20.757	446.303	2.949
March	*SEFV*	0	-5.971	*RSH*	2	2.698	20.772	446.266	2.947
				2014	**and**	**2013**			
February	*SEFV*	0	-5.773	*RSH*	2	2.6113	19.99	435.05	2.87
January	*SEFV*	0	-5.7707	*RSH*	2	2.6116	19.98	434.56	2.87
December	*SEFV*	0	-5.82	*RSH*	2	2.6259	20.24	439.39	2.87
November	*SEFV*	0	-5.8412	*RSH*	2	2.6309	20.36	441.66	2.87
October	*SEFV*	0	-5.8509	*RSH*	2	2.6303	20.43	443.31	2.88
September	*SEFV*	0	-5.8962	*RSH*	2	2.6421	20.67	447.95	2.87
August	*SEFV*	0	-5.949	*RSH*	2	2.6543	20.96	453.76	2.87

Table 4. The models for MS.

Month	C_1	t_1	b_1	C_2	t_2	b_2	*c*	*d*	**sterr,$**
				2012					
October	*SEFV*	0	-7.93	*ORPR*	2	4.415	25.226	420.919	3.468
September	*SEFV*	0	-7.90	*ORPR*	2	4.399	25.137	420.060	3.468
August	*SEFV*	0	-7.96	*ORPR*	2	4.425	25.343	423.817	3.447
July	*SEFV*	0	-7.96	*ORPR*	2	4.445	25.258	420.687	3.440
June	*SEFV*	0	-8.01	*ORPR*	2	4.449	25.526	426.655	3.437
May	*SEFV*	0	-8.01	*ORPR*	2	4.452	25.540	426.579	3.434
April	*SEFV*	0	-7.97	*ORPR*	2	4.419	25.492	427.246	3.422
March	*SEFV*	0	-8.00	*ORPR*	2	4.431	25.609	429.254	3.421
				2014	**and**	**2013**			
February	*SEFV*	0	-7.569	*ORPR*	2	4.2574	23.66	398.90	3.35
January	*SEFV*	0	-7.605	*ORPR*	2	4.2773	23.81	400.40	3.33
December	*SEFV*	0	-7.735	*ORPR*	2	4.3249	24.43	411.33	3.28
November	*SEFV*	0	-7.732	*ORPR*	2	4.3197	24.44	411.77	3.29
October	*SEFV*	0	-7.740	*ORPR*	2	4.3231	24.47	412.41	3.30
September	*SEFV*	0	-7.754	*ORPR*	2	4.3227	24.57	414.62	3.31
August	*SEFV*	0	-7.810	*ORPR*	2	4.3494	24.80	418.21	3.32

Table 5. The monthly models for JPM.

Month	C_1	t_1	b_1	C_2	t_2	b_2	*c*	*d*	**sterr,$**
				2012					
October	*F*	4	-1.856	*ORPR*	2	0.993	7.037	116.907	2.955
September	*F*	4	-1.859	*ORPR*	2	1.006	6.965	114.846	2.932
August	*F*	4	-1.861	*ORPR*	2	1.018	6.898	112.917	2.914
July	*F*	4	-1.863	*ORPR*	2	1.024	6.873	112.112	2.912
June	*F*	4	-1.865	*ORPR*	2	1.024	6.883	112.342	2.912
May	*F*	4	-1.863	*ORPR*	2	1.024	6.877	112.182	2.912
April	*FH*	4	-1.254	*FAB*	2	1.770	10.219	-12.460	2.905
March	*F*	4	-1.878	*ORPR*	2	1.051	6.791	109.260	2.839
				2014	**and**	**2013**			
February	*SEFV*	0	-4.989	*RPR*	3	2.448	17.79	369.06	3.28
January	*SEFV*	0	-4.928	*RPR*	3	2.418	17.58	364.86	3.29
December	*SEFV*	0	-4.920	*RPR*	3	2.409	17.59	365.33	3.31
November	*SEFV*	0	-4.856	*RPR*	3	2.383	17.33	359.95	3.29
October	*SEFV*	0	-4.809	*RPR*	3	2.366	17.11	355.74	3.27
September	*SEFV*	0	-4.769	*RPR*	3	2.349	16.96	352.67	3.29
August	*SEFV*	0	-4.809	*RPR*	3	2.375	17.05	354.26	3.30

Table 6. The monthly models for BEN.

Month	C_1	t_1	b_1	C_2	t_2	b_2	*c*	*d*	**sterr,$**
				2012					
October	*FB*	4	-7.333	*O*	9	-1.519	69.578	1536.224	7.365
September	*FB*	4	-7.319	*O*	9	-1.515	69.428	1533.079	7.361
August	*FB*	4	-7.301	*O*	9	-1.513	69.275	1529.960	7.353
July	*FB*	4	-7.299	*O*	9	-1.515	69.286	1530.175	7.353
June	*FB*	4	-7.311	*O*	9	-1.515	69.375	1532.037	7.350
May	*FB*	4	-7.301	*O*	9	-1.513	69.304	1529.705	7.343
April	*FB*	4	-7.303	*O*	9	-1.515	69.361	1530.410	7.337
March	*FB*	4	-7.309	*O*	9	-1.513	69.312	1531.360	7.270
				2014	**and**	**2013**			
February	*FB*	4	-2.387	*O*	9	-0.499	22.75	504.08	2.50
January	*FB*	4	-2.417	*O*	9	-0.509	23.07	511.20	2.48
December	*FB*	4	-2.439	*O*	9	-0.517	23.31	516.42	2.46
November	*FB*	4	-2.422	*O*	9	-0.512	23.14	512.74	2.46
October	*FB*	4	-2.421	*O*	9	-0.512	23.13	512.44	2.47
September	*FB*	4	-2.419	*O*	9	-0.511	23.10	511.84	2.48
August	*FB*	4	-2.436	*O*	9	-0.516	23.28	515.74	2.48

Figure 4 depicts five models as compared to the relevant actual prices since July 2003. We also plotted the high/low monthly prices in order to illustrate the level of fluctuations of the intermonth prices. One may model the monthly closing prices as well as the high, low, average, etc. prices and likely obtain slightly different models. As mentioned above, we have estimated R^2 for five models, as Table 1 lists. All coefficients of determination are larger than 0.7, with three from five models having $R^2>0.9$. In order to prove that these statistical estimates for our quantitative models are not biased we have tested them for cointegration between actual and predicted series. The Johansen tests for cointegration rank have shown cointegration rank 1 in all cases (Table 8). We have also tested the model residual time series (see Figure 5) for unit roots (Table 9) and found that they are I(0) processes. Therefore the predicted and observed series are cointegrated for all banks and R^2 in Table 1 are not biased.

Table 7. Cross correlation coefficients for seven CPI time series and their first differences. Original series and their first differences include 128 readings.

	dF	*dFB*	*dSEFV*	*dORPR*	*dRSH*	*dO*	*dRPR*
dF	1						
dFB	0.996	1					
dSEFV	0.448	0.453	1				
dORPR	0.096	0.095	0.295	1			
dRSH	0.141	0.123	0.202	0.384	1		
dO	-0.168	-0.171	0.054	-0.006	0.085	1	
dRPR	0.232	0.236	0.286	0.774	0.251	-0.042	1

Table 8. Results of the Johansen cointegration rank test

Company	Cointegration rank	LL	Eigenvalue	Trace statistic	5% critical value
BAC	1	-516.168	0.24862	1.4023*	9.42
BEN	1	-463.647	0.20147	6.5045*	9.42
GS	1	-877.044	0.22139	4.7022*	9.42
JPM	1	-482.456	0.18114	6.4002*	9.42
MS	1	-542.956	0.15814	2.2413*	9.42

Table 9. Results of the Phillips-Perron unit root test for model residuals

Company	z(t)	z(t) 1% critical	z(rho)	z(rho) 1% critical
BAC	-5.75	-3.50	-52.49	-19.89
BEN	-5.74	-3.50	-52.57	-19.89
GS	-6.03	-3.50	-53.67	-19.89
JPM	-5.70	-3.50	-52.41	-19.89
MS	-5.69	-3.50	-50.90	-19.89

Discussion

Two years ago we discussed the future stock prices for BAC, BEN, GS, JPM, and MS depending on the evolution of defining consumer price indices. The correlated movement in BAC and MS stock prices was explained by similarity in defining CPIs with equal time lags. This observation is valid after 16 months with the same ratios of CPI coefficients in (3) and (4): (b_1/b_2) is -2.21 (-2.23 in 2012) for BAC and -1.78 (-1.65) for MS. The closeness of these ratios still guarantees similar evolution of both prices.

Considering the influence of the same change in *SEFV* on absolute price change we reveal significant differences compared to October 2012. One unit change in *SEFV* currently forces a \$2.86 (\$5.9) change in BAC and \$4.1 (\$8) change in MS. Depending on the future absolute evolution of *SEVF* and its evolution relative to *RSH* (*ORPR* for MS) one may quantitatively estimate the performance of BAC and MS.

Goldman Sachs has the same defining CPIs (*F* and *ORPR*), the same time lags and ratio of coefficients is -1.23 (-1.23). Its stock price fell lower from its peak in 2007 and recovered in 2009 to 0.8 of the pre-crisis level due to quick and deep fall in food prices. The fall in GS price in 2011 was induced by a surge in food prices. Since 2012, d*F* has been increasing at a slightly lower rate while d*ORPR* retained its momentum. As a result, GS price has been growing at a good pace. When the food price index falls, one should choose GS. The model for JPM has changed from *F* to *SEVF* and from *ORPR* to *RPR*. In sense of defining CPIs and their lags the JPM model is now closer to those for BAC and MS. According to the ratio of the current share price to b_1, JPM is more sensitive to *SEFV:* one unit change forces and \$11 or 20% change. It is interesting to observe further transitions in the JPM model. One cannot exclude JPMorgan Chase undergoes deep restructuring, which makes it similar to BAC and MS.

As in 2012, the best fit BEN model is based on the consumer price index of other goods and services (*O*), which has a quite specific shape with a high-amplitude step between February and April 2009. Therefore, the first difference of *O* does not correlate with any other involved index. For BEN, the step in *O* series is associated with a sharp fall in the stock price nine months before, as the negative coefficient in Table 6 assumes. We interpret this observation as an indication that BEN stocks are driven by some forces different from other four companies. As we foresaw in 2012, the high correlation with JPM has dropped significantly due to mediocre growth in the BEN share price during the last 16 months.

All five models for financial companies demonstrate excellent performance since 2010. This observation is a good validation of our pricing model of U.S. stocks. One can formulate a strategic approach using the deterministic models and predict the relevant returns with their uncertainties as based on the projected evolution of CPI components.

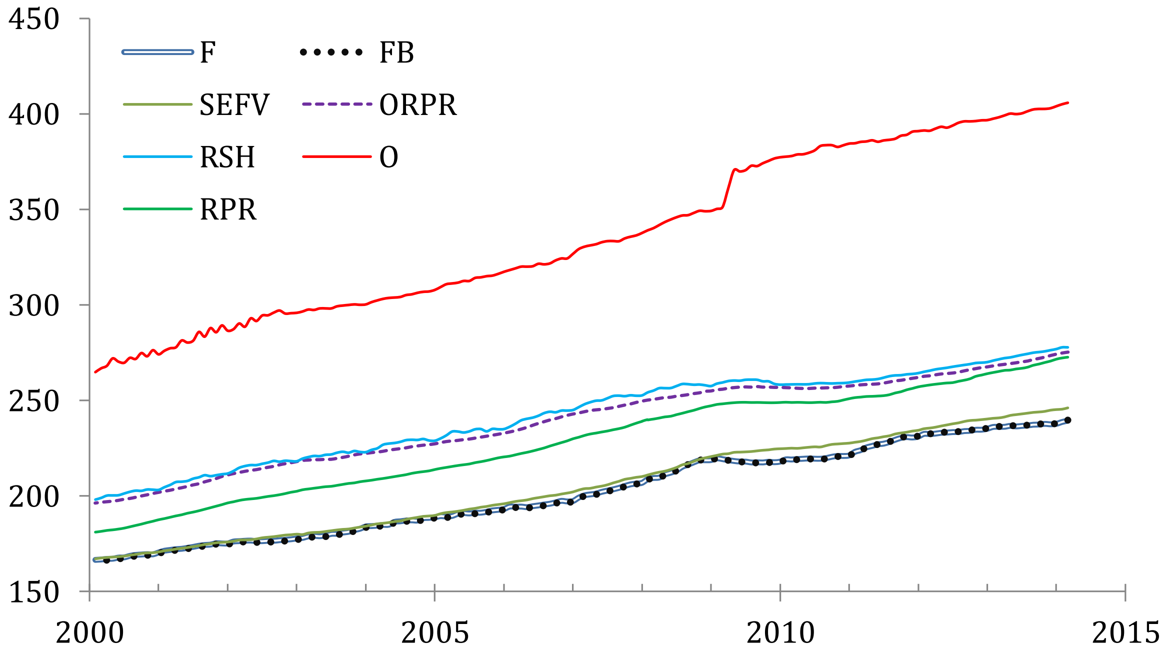
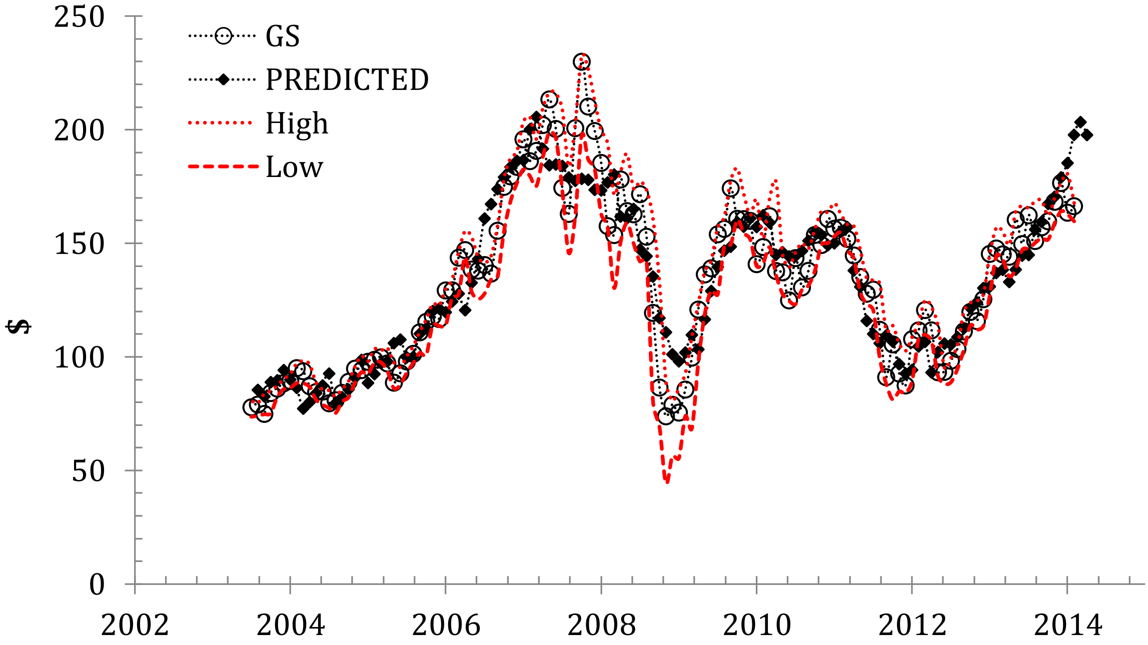


Figure 3. The evolution of all defining CPIs. Notice F and FB are practically identical.


GS
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2012
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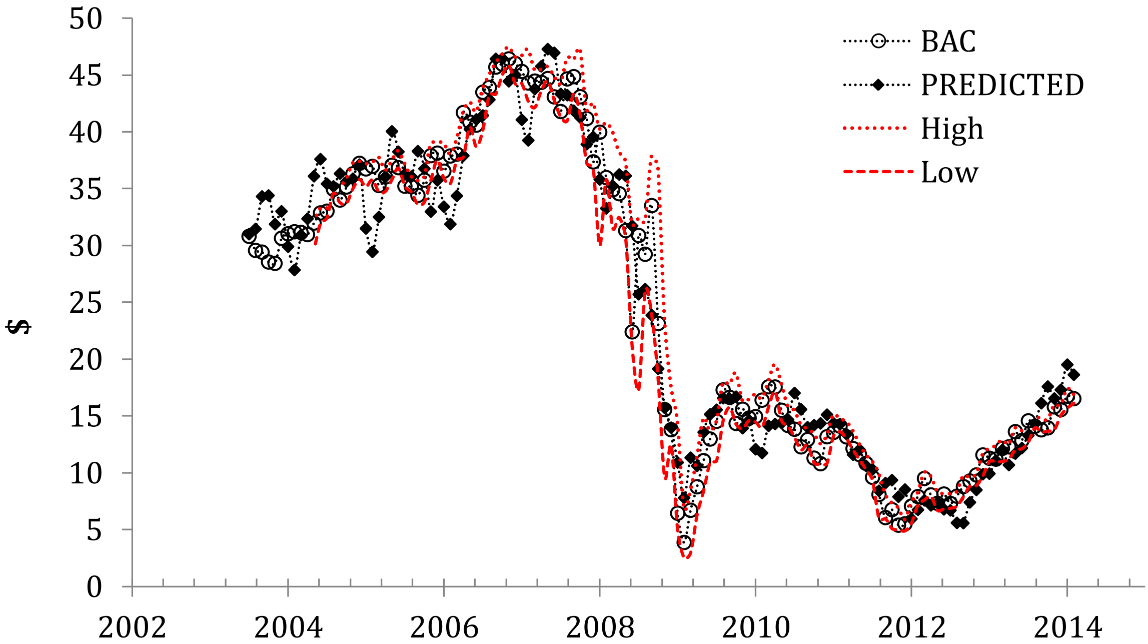
BAC
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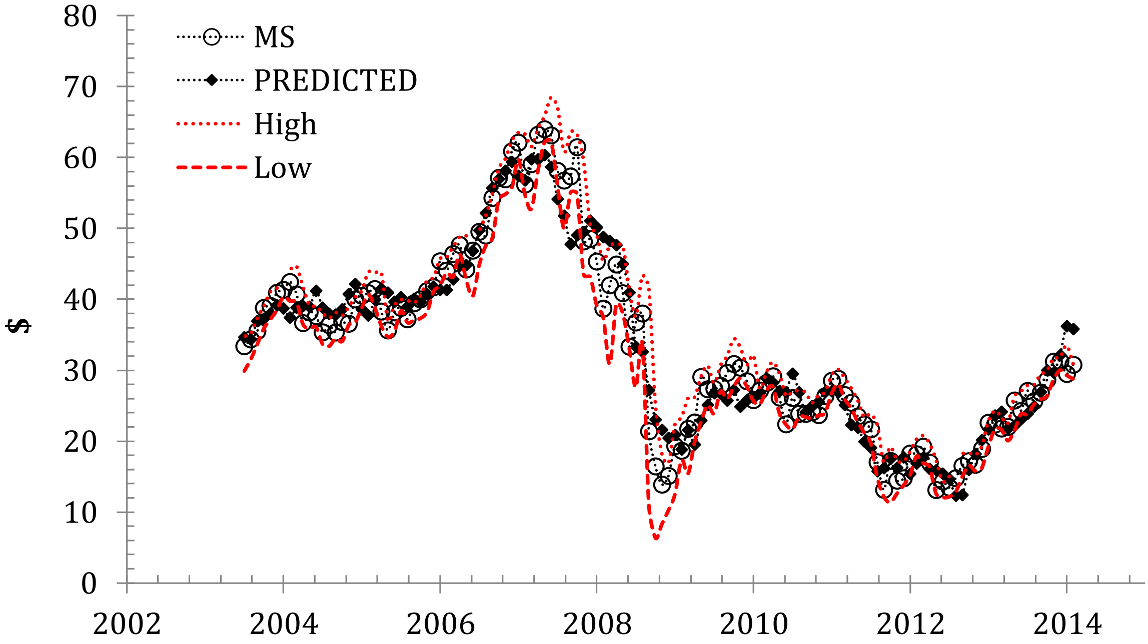

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MS
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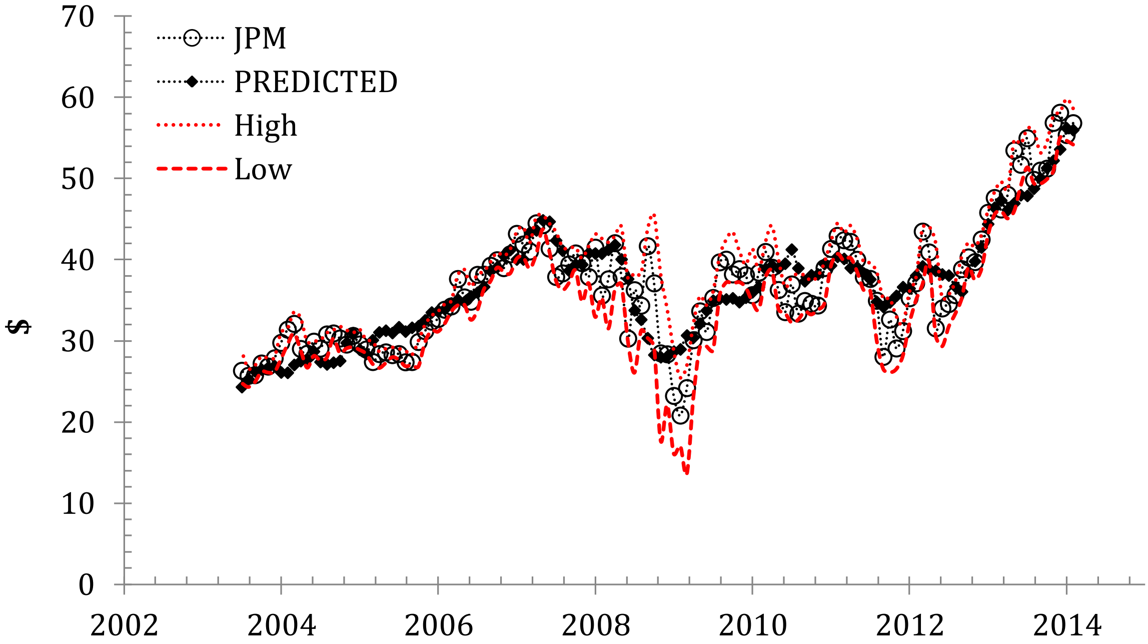

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JPM
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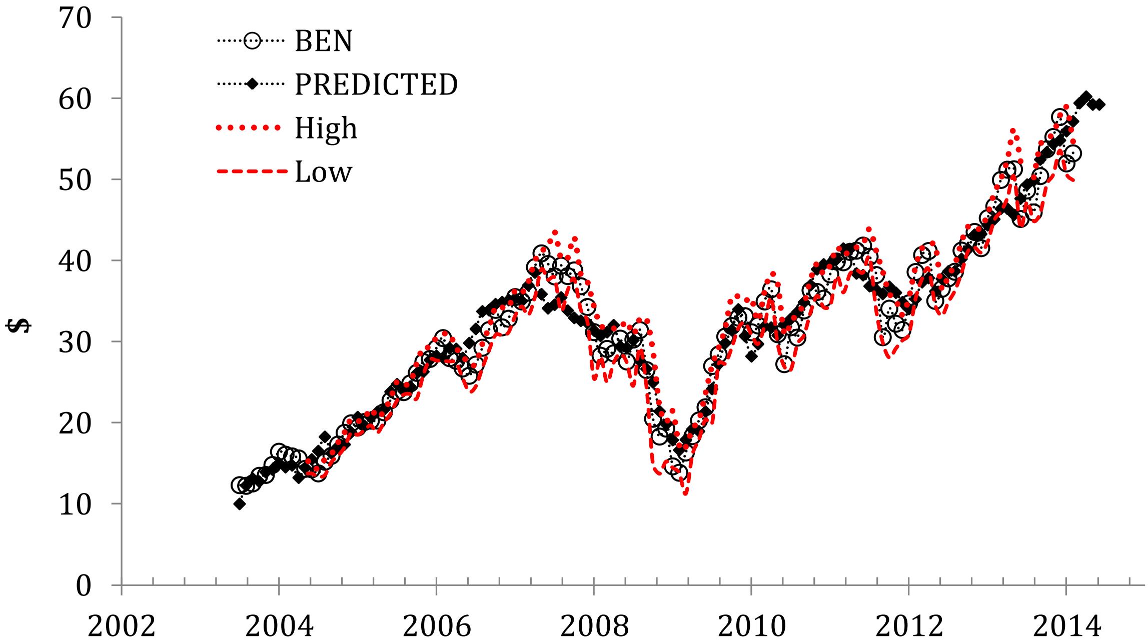

Figure 4. Observed and predicted share prices together with their high/low monthly prices.

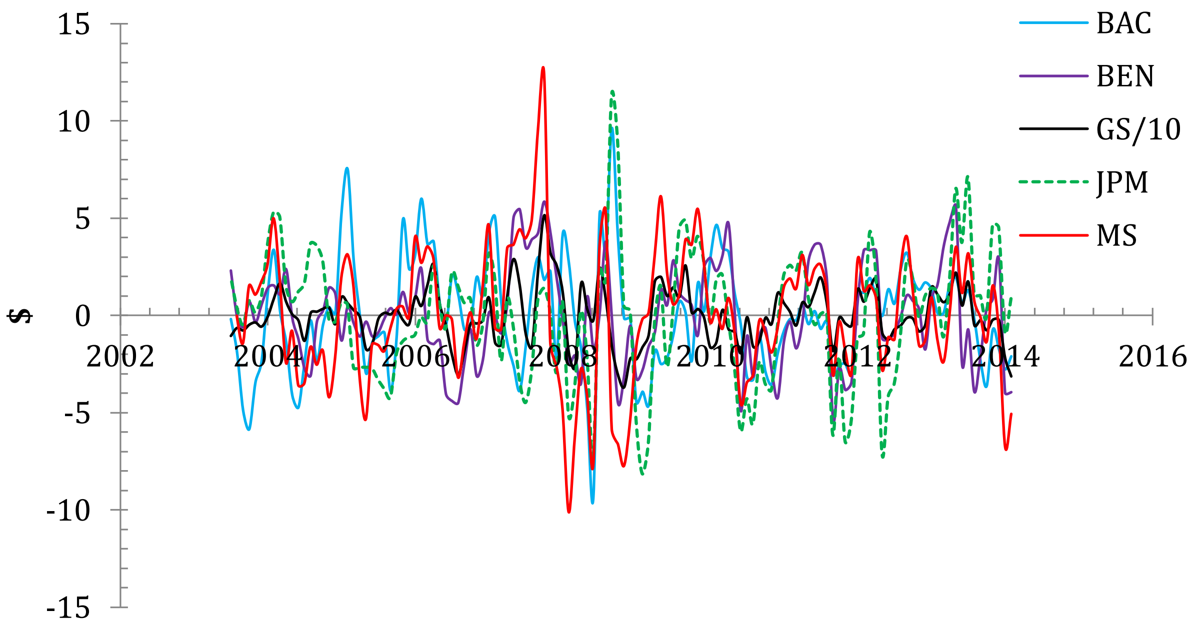

Figure 5. The residual model errors.

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