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Time-dependent selection of important economic indicators over stock prices

Abstract

While stock returns are related to macroeconomic indicators, the prediction of future stock returns from news of these indicators has proved unsuccessful since the explanatory power of such news is low. One of the reasons is said to be that the effect of macroeconomic news changes over time.

This paper improves the explanatory power by introducing a time-dependent model of the effect of news of macroeconomic indicators. The model is based on a combination of robust, stepwise and rolling regressions. In addition to the model, the authors extend the range of indicators under consideration from that of previous studies. Using monthly data, we show that our model has explanatory powers ranging from 0.1 to 0.8, which is higher than in previous studies. The paper also finds that the members and coefficients of important indicators are stable in the short term, reflecting the stability of a short-term macroeconomic condition, while they change with time in the long run, reflecting phases of the business cycle.

In addition, the authors create a prediction model of future return and risk. It is shown that our return prediction is better than previous studies if an exact prediction of economic indicators is possible. Value-at-risk based on our prediction is more reasonable than value-at-risk based on the usual prediction. Our model enables us to use economic indicators for the purpose of risk and return analysis.

Keywords: return forecast, economic indicator, macroeconomic model.
JEL Classification: G14, G17, C51, C52.

Introduction

It is a widespread idea to use macroeconomic news to explain stock prices. In fact, most economists, market analysts and other market participants use macroeconomic data to explain the movements of stock markets. They use these data not only to give reasonable explanations for past movements, but also to give a persuasive scenario for future stock prices. While other factors such as policy decisions or weather effects are also important, macroeconomic factors seem to be the primary choices as explanatory variables of stock prices. However, previous studies do not give enough evidence for the effectiveness of this intuitive approach to predict returns.

Valuation theories of stocks seem to suggest a relation between stock prices and the macroeconomic environment. For example, the dividend discount model assumes that a stock price p is the summation of discounted expected dividends in the future. In a simple form, it can be described as

$$p = \frac{E[c]}{k - g}, \qquad (1)$$

where c is the dividend, k is the discount rate, and g is the growth rate. Even in this simple model, movements of stock prices seem to follow changes of the discount rate and future dividends, which will be caused by changes of macroeconomic indicators.

Empirical studies have spent much effort identifying important macroeconomic indicators. Inflation and money growth were documented to have a negative impact on stock prices in early studies (for example, Bodie, 1976; Fama, 1981). Chen, Roll and Ross (1986) report five factors: growth rate of industrial production, expected inflation, unexpected inflation, bond default risk premium, and term structure spread. Culter, Poterba and Summers (1989) show the effect of industrial production on stock returns.

The problem with the above studies is that explanatory powers of the information before returns realized are too small. For example, Culter et al. report that only one tenth of monthly stock returns can be explained from monthly macroeconomic data. They also report that the explanatory power can be improved to 40 or 50 percent by using ex post information or by changing the data frequency to annual. This result suggests that macroeconomic indicators are actually related to stock prices. However, for the purpose of prediction, we cannot use ex post data. No other past studies that we have checked give an explanatory power much better than 0.1.

McQueen and Roley (1993) consider that constant coefficient models cause failures in identifying significant macroeconomic news. They define economic status based on industrial production, and suggest that the same announcements have different implications according to the economic status. They report that when the economy is strong, good news about the real economy has a negative effect on stock returns, while it has a positive effect when the economy is weak. These different reactions to the same news are explained by the different (expected) reactions of monetary policy. When the economy is expanding, positive news about the economy increases the possibility of tighter monetary policy, that is, higher discount rates k in equation (1). When the economy is contracting, negative news increases the possibility of looser monetary policy, that is, lower discount rates k in equation (1). Boyd, Jagannathan and Hu (2005) report that unemployment has a strong positive effect on stock prices during economic expansion periods, while it has a weak effect during contraction periods. Andersen (2007) shows that the positive surprise of nonfarm payrolls has a negative effect on five-minute returns after an announcement during an economic expansion, but has a positive effect during an economic recession.

Although not the focus of this paper, another possible factor affecting the relation between stock prices and macroeconomic events is volatility. Flannery and Protopapadakis (2002) apply GARCH models to daily U.S. stock returns. They use not only GARCH models but also macro announcements, finding three nominal indicators (CPI, PPI, and monetary aggregate) and three real indicators (balance of trade, employment report, and housing starts) as important factors.

In practice, macroeconomic announcements undergo revisions. The scale of these revisions is comparable to that of initial announcements, but they take many months or even years to reach their final values. Gilbert (2011) shows that revisions of nonfarm payroll actually have an effect on stock prices.

While efforts of these preceding studies, debate about the predictivity of returns by economic indicators is still controversial. In the special issue of the Review of Financial Studies discussing about forecasting of the equity premium, Welch and Goyal (2008) comprehensively reexamine the performance of indicators which preceding studies suggest as predictor of equity premium. In their analysis, out-of-sample prediction based on these indicators cannot beat simple historical mean. This result is surprising and evoking debates. For example, Campbell and Thompson (2008) argue in the same special issue that prediction based on some indicators actually gives higher returns than that based on simple historical return.

In addition, Welch and Goyal (2008) argue that the prediction based on indicator suggested by other studies is unstable and depends on periods. For example, they show that it is the 1973-75 Oil Shock that gives the prediction performance to most of the suggested indicators, and that there is no big excess return from the prediction after the Shock. While this result implies that it is impossible to obtain a stable prediction model for a long period, it does not deny the importance to capture specific returns stemming from special conditions such as the Oil Shock.

In summary, in order to construct a good model to predict stock returns, there remain two problems to be solved. One is low explanatory power. The other is instability of effects of important indicators.

In this paper, we aim to introduce a time-dependent approach to estimate the effect of macroeconomic indicators and identify important ones. We also aim to extend the universe of macroeconomic indicators in analysis more widely than past studies. We use monthly data and combine robust, stepwise and rolling regressions. We find that the set of important indicators changes with time, and that the importance of an indicator reflects the status of the economy. In addition, we show that this set of indicators can explain out-of-sample returns, and that value at risk (VaR) based on the set can be a reasonable risk measure.

This paper is organized as follows. In sections 1 and 2, we introduce the model and the data we used, respectively. In section 3, we describe the method to identify important indicators, and show the result. In section 4, we discuss the out-of-sample prediction and risk measure based on the macro indicators. In the final section, we summarize our discussion.

1. Model

In this paper, we focus on the "surprise" of a macroeconomic indicator. If there is only one indicator, this model is expressed as:

$$r_t = E[r_t|t-1] + \beta z_t + \varepsilon_t, \tag{2}$$

where t denotes time, r_t is the stock return from $t-1$ to t, z_t is the "surprise" of the indicator during this period, and ε_t is a residual term. Conditional expectation $E[r_t|t-1]$ denotes the expected return at time $t-1$, reflecting all information available at time $t-1$. This information includes both deterministic factors such as interest rates, and nondeterministic factors such as future economic status. Equation (2) is easily extended to multivariate models.

Assuming $\varepsilon_t = 0$ and taking the conditional expectation of equation (2) at time $t-1$, we obtain $E[z_t|t-1] = 0$. Since we consider the surprise of a macroeconomic indicator, it is natural to define z_t as:

$$z_t = Z_t - E[Z_t|t-1], \tag{3}$$

where Z_t is the realized value of the indicator and $E[Z_t|t-1]$ is the conditional expectation of the indicator at time $t-1$. Conditional expectation $E[Z_t|t-1]$ is typically observed as the analyst forecast. Note that Z_t in equation (3) should not be the total of the initial and revised announcements, since revisions may have different effects to those expected from initial announcements, as discussed in the next section.

Conditional expectation $E[Z_t|t-1]$ is considered to denote a predetermined source of return. For example, if a risk-free asset exists, then stock return r_t should be evaluated in comparison with the risk-free rate r_f. In addition, financial variables such as credit premium, term premium, dividend yield, and own lagged stock return are reported as the source of predetermined return. However, the explanatory powers of these variables are not so large. Therefore, for simplicity, we basically assume this predetermined return is constant:

$$E_0 = E[r_t|t-1] = \alpha. \tag{4}$$

We also check the case

$$E_1 = E[r_t|t-1] = \alpha + \beta_{TB}TB_{t-1} + \beta_{CP}CP_{t-1} + \\ + \beta_{TP}TP_{t-1} + \beta_r r_{t-1}, \tag{5}$$

where TB denotes three-month Treasury bills rate, CP denotes credit premium, and TP is the term premium. The last term denotes lagged own stock return. We see later that the explanatory power of equation (5) is low and that the choice of predetermined return does not affect our conclusion.

Unfortunately, efforts based on equation (2) have not been very successful. Instead, we consider the case that coefficient β in equation (2) is not constant but time-dependent, as:

$$r_t = E[r_t|t-1] + \beta_t z_t + \varepsilon_t. \tag{6}$$

Actually, this time-dependent model is supported by several studies (McQueen et al., 1993; Boyd et al., 2005).

In this paper, we incorporate time-dependency by adopting a dynamic model for selecting important indicators. The model is described as

$$r_t = E[r_t|t-1] + \sum_{i \in I_{t_0}} \beta^i_{t_0} z^i_t + \varepsilon_t, \tag{7}$$

where t denotes month and $i \in I_{t_0}$ denotes the index of a macroeconomic indicator. The "important indicators'" index set I_{t_0} consists of indicators that are statistically selected based on information available at time t_0. Coefficients $\beta^i_{t_0}$ are also assumed to be time-dependent and statistically selected based on information available at time t_0. As a result, the model described by equation (7) incorporates a time-dependent effect of economic indicators. In section 3, we will see how to select the indicator set I_{t_0}, in which the sample window length is T (the in-sample period is taken as $t_0 - T + 1 < t \le t_0$).

2. Data

In monthly analysis based on equation (7), we consider t_0 from January 2001 to December 2010. We use S&P 500 Futures (CME, closest contract), Russell 3000 and Dow Jones Industrial Average (DJIA) as stock prices.

For TB, TP and CP in equation (5), we use the data provided in H. 15 by the Federal Reserve Board. TB is 3M TB rate in the secondary market. TP is given as the 10-year Treasury rate minus the 3M TB rate. CP is given as the corporate bond rate of AAA companies minus that of BAA companies.

We use 39 macroeconomic indicators listed in Table 1, whose coverage includes indicators not suggested by any other previous studies we have checked. The realized data, or Z_t in equation (3), of these indicators are obtained from the initial source. As for the forecast values, $E[Z_t|t-1]$ in equation (3), we use the analyst consensus obtained from Briefing (www.briefing.com) and Bloomberg. We use Briefing.com primarily and use Bloomberg if Briefing is unavailable.

2.1. Revisions. Macroeconomic indicators undergo revisions. Gilbert (2011) reports that revisions actually have an effect on stock prices. Significant revisions sometimes take place many months after initial announcements. At the same time, it is shown that revisions may have different effects to those expected from initial announcements.

In this paper, we generally ignore the effect of revisions for two reasons. First, the effect of a revision is small compared to the initial announcement. Second, the effect of revisions on prices is too complicated to allow revisions to be taken into account. For example, if we simply take the total of the value of the initial announcement and the value of revisions in order to incorporate the effect of revisions, we get an incorrect idea of the effect of revisions.

2.2. Cleanup of monthly data. In Table 1, not all indicators are announced monthly. For example, GDP and productivity are quarterly, while initial claims are weekly. As for GDP, there are basically three announcements for the same period. For example, GDP of the first quarter of 2001 is announced on April 27, 2001 as the first estimate, on May 25, 2001 as the second estimate and on June 29, 2001 as the third estimate. Combining all of them, we obtain monthly data. Likewise, we can combine primary and modified productivity data into one series. These indicators gather so much attention that market participants make forecasts for each revision. Therefore, we simply treat these indicators as original sources, not as revisions.

Table 1. Monthly macroeconomic surprises and *p*-values as predictors of stock returns

ID	Indicator	Time	Obs.	*p*-values		
				OLS	Bisquare	Huber
1	Average workweek	8:30	119	0.55	0.58	0.54
2	Building permits	8:30	113	0.26	0.66	0.55
3	Business inventories	8:30	120	0.50	0.23	0.33
4	Capacity utilization	9:15	120	**0.00**	0.10	**0.03**
5	Chicago PMI	10:00	120	0.10	0.49	0.28
6	Construction spending	10:00	117	0.44	0.58	0.55
7	Construction confidence	10:00	120	**0.08**	0.41	0.21
8	Consumer credit	15:00	119	1.00	1.00	1.00
9	Core CPI	8:30	120	0.89	0.80	0.84
10	Core PPI	8:30	119	0.47	0.67	0.56
11	CPI	8:30	120	0.53	0.44	0.43
12	Durable orders	8:30	120	**0.05**	**0.02**	**0.03**
13	Existing home sales	10:00	116	**0.05**	**0.02**	**0.03**
14	Factory orders	10:00	111	0.21	0.54	0.40
15	GDR	8:30	119	0.71	0.84	0.84
16	GDR deflator	8:30	115	0.60	0.44	0.52
17	Hourly earnings	8:30	118	0.47	0.32	0.31
18	Housing starts	8:30	119	0.13	0.29	0.29
19	Industrial production	9:15	120	**0.00**	**0.06**	**0.01**
20	Initial claims	8:30	120	**0.00**	**0.00**	**0.00**
21	ISM index	10:00	120	0.27	0.98	0.65
22	ISM services	10:00	120	0.75	0.71	0.69
23	Leading indicators	10:00	120	0.46	0.91	0.77
24	Michigan sentiment	10:00	120	0.19	0.37	0.25
25	Michigan sentiment-rev.	10:00	107	0.41	0.42	0.41
26	New home sales	10:00	120	0.20	0.22	0.24
27	Nonfarm payrolls	8:30	120	0.59	0.74	0.80
28	NY Empire Manufacturing Index	8:00	92	**0.01**	0.12	**0.06**
29	Personal income	8:30	91	0.20	0.27	0.28
30	Personal spending	8:30	91	0.91	0.57	0.66
31	Philadelphia Manufacturing Index	10:00	120	**0.01**	**0.09**	**0.03**
32	PPI	8:30	119	0.92	0.70	0.74
33	Productivity	8:30	79	0.24	0.38	0.33
34	Retail sales	8:30	120	**0.06**	**0.01**	**0.02**
35	Retail sales ex-auto	8:30	120	0.17	**0.07**	**0.08**
36	Trade balance	8:30	120	1.00	1.00	1.00
37	Teasury budget	14:00	120	1.00	1.00	1.00
38	Unemployment rate	8:30	120	**0.01**	**0.00**	**0.00**
39	Wholesale inventories	10:00	119	0.97	0.94	0.93

Notes: S&P 500 Future is used as stock returns. Boldface figures are below 0.1.

As for weekly data such as initial claims, we adopt the sum for a given month as the value of the month. For example, in January 2001, there were four announcements of initial claims (Jan. 4: +25,000, Jan. 11: -25,000, Jan. 18: -49,000 and Jan. 25: -14,000, where values were “surprises”). We use -63,000 as the “surprise” of initial claims in January 2001. In addition, when there are more than two announcements of monthly data in a single calendar month, we use the sum of them as the value of the month. For example, factory order was announced twice during August 2001 (Aug. 2: -1.3% for June, Aug. 31: +0.6% for July, where values were surprises) and was not announced in September 2001. In this case, we use -0.7% as the value of August 2001 and N/A as that of September 2001. We suppose that this summation is valid since these summands do not include revisions.

In order to make regressions meaningful, we ignore indicators that contain N/A of more than one third of the regression period. One of these excluded indicators is the S&P Case-Shiller Index, which received great attention during the subprime mortgage crisis. However, since this index did not have enough forecast values before the crisis, we could not use it. As a result, we have obtained 39 time series in Table 1.

2.3. Unit-root test, zero mean test and correlation of surprises. We adapt an augmented Dickey-Fuller test to return series and economic surprises in order to check stationarity. As a result, we confirm that all economic surprises show no unit-root with one percent confidence level. In addition, using t-statistics we also confirm the zero mean hypothesis of returns and surprises.

The correlations between these surprises are generally weak. However, the correlation between building permits and housing starts, capacity utilization and industrial production, core CPI and CPI, and retail sales and retail sales ex auto exceed 0.50.

3. Method

In this section, we introduce the selection model for important indicators, that is, for the selection of I_{t_0} and the determination of β_{t_0} in equation (7). First, we introduce the selection for the entire period using robust and stepwise regression. Next, we apply this approach to rolling windows, which we call rolling regression. In this section, we suppose the predetermined return $E[r_t|t-1]$ is constant as equation (4).

3.1. Robust regression. In order to find candidates as important indicators, we first consider the single regression model of equation (2) and apply robust regression. We use three weight functions: ordinary least squares (OLS), bisquare weight with parameter $k = 4.685$ and Huber weight with parameter $k = 1.345$. N/A values are ignored.

Table 1 also shows the p-values of the entire period regression for the case of S&P 500 future as the stock return. Some indicators show p-values lower than 10% for several weight functions. We select indicators whose p-values are less than 10% for at least one weight function as a candidate for I_{t_0}.

3.2. Stepwise regression. We use (ordinary linear) stepwise regression to determine I_{t_0}. At first, we normalize each economic indicator before regression and substitute zero into N/A entries assuming that N/A is equivalent to no news. Then, we carry out regression of equation (7) on the candidates obtained in the robust regression. Next, we add and delete series among 39 economic indicators, using the standard stepwise regression method. We use $p = 0.05$ as the entry level and $p = 0.10$ as the deletion level. Finally, we obtain the final result of in-model indicators I_{t_0} and compute the explanatory power (R^2) and adjusted R^2 of equation (7).

The result for the entire period is shown in Table 2. The set I_{t_0} does not depend very much on the index series. The explanatory power and adjusted R^2 are both about 0.30 for each index, which are better results than in past research.

In Table 2, industrial production and unemployment rate appear. These agree with the results in preceding studies that these indicators are important. Initial claims also appear in the table. Initial claims usually attract market attention in order to forecast unemployment rate. Note that nonfarm payrolls do not appear in the table.

Table 2. In-model variables in the entire-period stepwise regression

	S&P Future	Russel 3000	DJIA
Average workweek			x
Existing home sales	x		x
Industrial productions	x	x	x
Initial claims	x	x	x
NY Empire Manufacturing Index	x	x	x
Philadelphia Manufacturing Index	x	x	x
Retail sales	x	x	x
Unemployment rate	x	x	x
R^2	0.34	0.33	0.36
Adjusted R^2	0.30	0.29	0.32
R^2 with top 2 PCs	0.34	0.33	0.36

We also see retail sales, existing home sales, NY Empire Manufacturing Index, and Philadelphia Manufacturing Index in the table. It is possible that the first two attract market attention because housing and consumption are said to be important factors in the U.S. economy. The latter two are indices of manufacturers. These indicators are said to be leading indicators that signal future economic status and therefore future stock price.

In order to check the effect of out-of-model indicators, we also compute the principal components of out-of-model indicators, add the top two to the model, and carry out regressions over this extended model. The bottom line of Table 2 ("R^2 with top 2 PCs") shows the explanatory power of this extended model, which is not improved.

3.3. Rolling regression and R^2. Next, we divide the entire period into rolling windows. These windows have the length T, which is set to T = 36, 48 or 60 months. Each window is distinguished by its last month denoted by t_0, and the month t in window t_0

satisfies $t_0 - T + 1 < t \leq t_0$. Indicators whose N/A entries are more than one fourth of the entire period during window t_0 are excluded from the window.

Based on the information during window t_0, we decide the set of important indicators I_{t_0}. The approach is the combination of robust and stepwise regressions described above. As a result, we obtain a set of important indicators $i \in I_{t_0}$ and their coefficients $\beta^i_{t_0}$ for each month t_0 in equation (7). We call this approach rolling regression.

Figure 1 shows the explanatory power of the model equation (7) obtained by the approach above. Although it varies from 0.1 to 0.8 depending on the period, the explanatory power is higher than 0.4 in more than half of the months considered, which is a higher level than found in previous studies (around 0.1). This difference can be explained by the number of indicators in I_{t_0}. Figure 2 shows that the number of indicators $n(I_{t_0})$ is approximately proportional to the explanatory power.

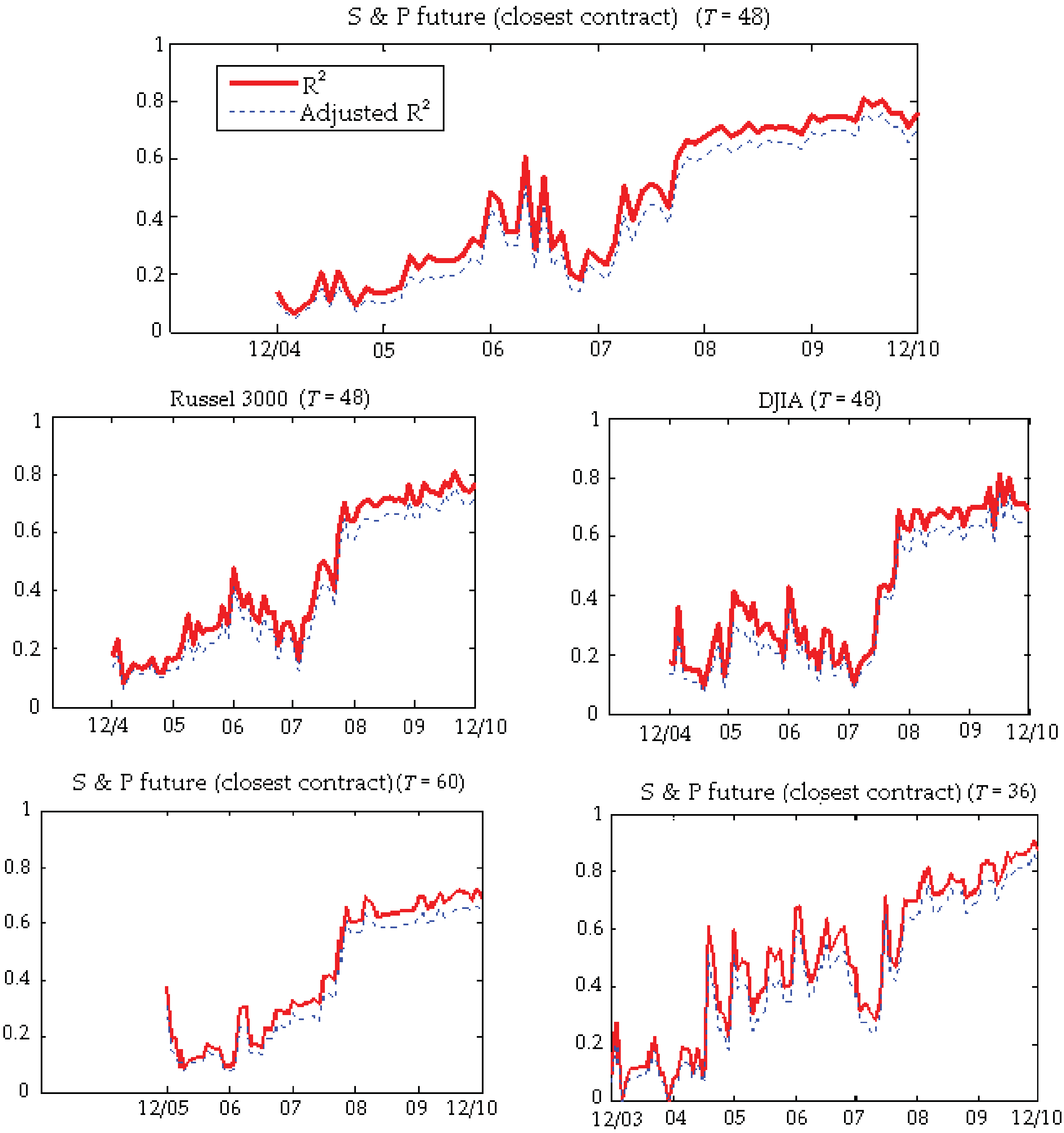


Fig. 1. Explanatory power in rolling regression

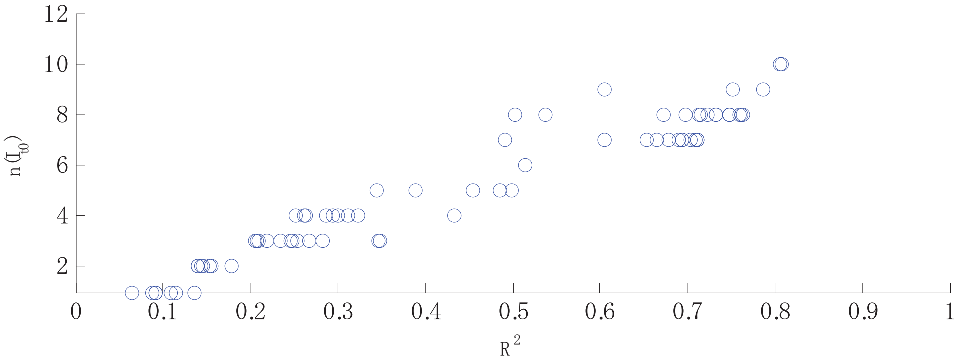


Fig. 2. Number of important indicators nI_{t_0} in rolling regression (S&P 500 Future, T = 48 case)

3.4. Time-development of important indicators. The set I_{t_0} changes every month. Some indicators appear frequently in I_{t_0}, while others do not. Table 3 shows the number of appearance in I_{t_0}, that is, $n(i) = n\{t_0; i \in I_{t_0}\}$ for each indicator i. In Figure 3, we show how specific indicators come into or go out from I_{t_0} with regard to month t_0 for the case of S&P 500 Future as stock price and $T = 48$.

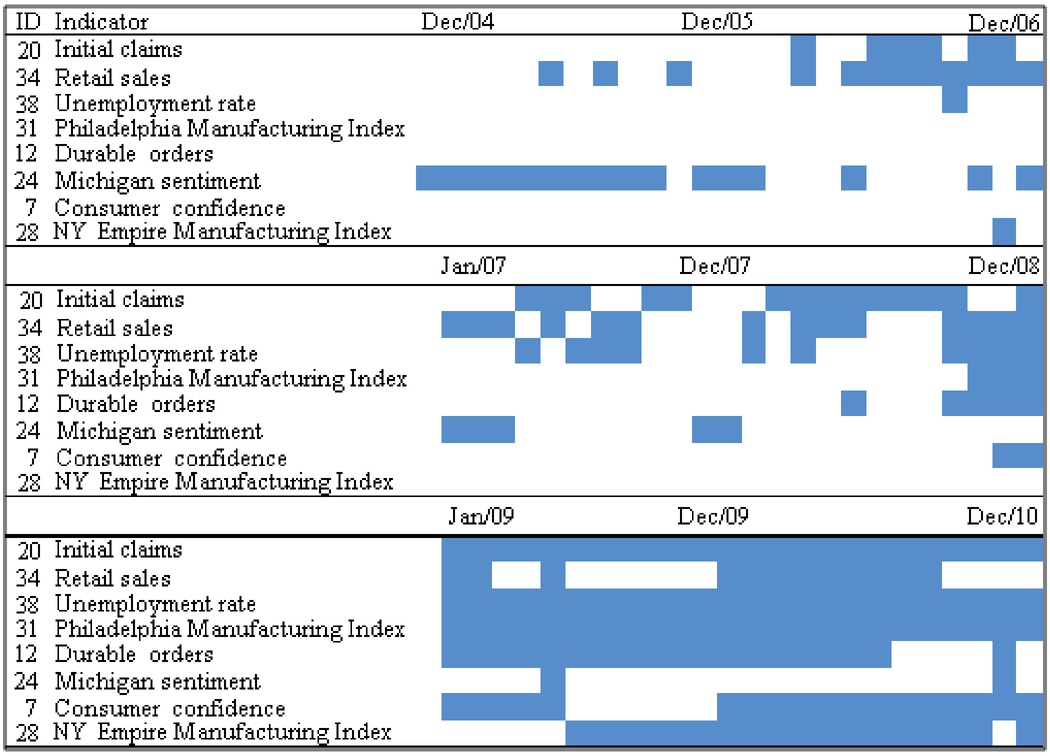
In Figure 3, the indicators included in the important indicators set I_{t_0} are shown by filled cells. According to Figure 3, the importance of a specific indicator does not change frequently. Once an indicator comes into I_{t_0}, it usually stays within I_{t_0} for several months. Once an indicator goes out from I_{t_0}, it does not usually come back to I_{t_0} for several months. For example, Michigan sentiment continues to appear before 2007, although it stopped appearing after that year. On the other hand, initial claims and unemployment rate are not important before 2008, while they almost always appear in the model after 2008.

Table 3. Number of appearances as an important indicator in rolling regression

ID	Indicator	T = 48			T = 60	T = 36
		S&P Future	Russell 3000	DJIA	S&P Future	S&P Future
1	Average workweek	1	1	1	0	0
2	Building permits	2	1	2	0	1
3	Business inventories	4	5	7	0	7
4	Capacity utilization	7	7	5	17	8
5	Chicago PMI	0	0	0	0	4
6	Construction spending	0	0	2	2	1
7	Construction confidence	20	17	11	22	9
8	Consumer credit	3	3	1	0	1
9	Core CPI	18	13	33	19	25
10	Core PPI	2	1	2	1	3
11	CPI	11	16	0	5	5
12	Durable orders	24	22	17	23	18
13	Existing home sales	6	5	10	4	5
14	Factory orders	8	8	7	1	15
15	GDR	0	4	0	3	7
16	GDR deflator	2	0	0	1	5
17	Hourly earnings	0	0	0	0	1
18	Housing starts	0	1	4	0	4
19	Industrial production	13	10	22	15	26
20	Initial claims	44	38	47	37	47
21	ISM index	17	18	13	13	12
22	ISM services	3	8	8	1	6
23	Leading indicators	5	5	6	6	2
24	Michigan sentiment	23	33	13	34	24
25	Michigan sentiment-rev.	2	0	0	0	1
26	New home sales	1	1	5	0	9
27	Nonfarm payrolls	11	5	2	1	1
28	NY Empire Manufacturing Index	19	18	15	12	24

Table 3 (cont.). Number of appearances as an important indicator in rolling regression

ID	Indicator	$T = 48$			$T = 60$	$T = 36$
		S&P Future	Russell 3000	DJIA	S&P Future	S&P Future
29	Personal income	3	1	2	0	1
30	Personal spending	2	2	4	0	0
31	Philadelphia Manufacturing Index	27	25	24	23	27
32	PPI	7	7	8	1	9
33	Productivity	0	0	0	0	0
34	Retail sales	38	29	30	33	25
35	Retail sales ex-auto	7	13	3	12	15
36	Trade balance	0	0	0	0	2
37	Teasury budget	4	3	19	6	5
38	Unemployment rate	35	30	31	32	28
39	Wholesale inventories	6	6	2	5	10



Note: Shadowed cells show that the indicator i is included in the important indicator set I_{t_0}.

Fig. 3. Important indicators in rolling regression (S&P 500 Future, *T* = 48 case)

This stability is also confirmed by Figure 4, which shows the time-development of coefficients $\beta_{t_0}^i$ for each indicator i. The horizontal axis represents time t_0 and the grayed zones represent months in which the indicator is included in the important indicators set I_{t_0} that is, month t_0 such that $i \in I_{t_0}$. Values of $\beta_{t_0}^i$ when $i \notin I_{t_0}$ are those in which we add indicator i into I_{t_0}. It is shown that β_{t_0} changes slowly.

This stability can be considered to reflect the property that the set of important indicators I_{t_0} is stable in the short term, for example, less than one year. This property is desirable for an explanation based on macroeconomic indicators, since economic conditions do not change very frequently. It is also consistent with the interests of market analysts or economists, whose predictions are usually for the near future, within six months or one year.

On the other hand, the set of important indicators I_{t_0} changes in the long run. This is desirable, since economic structures change annually or with a longer frequency. By checking the set of important indicators I_{t_0}, we can discuss the changes of economic status or phases of the business cycle.

In Figures 1 and 2, the number of important indicators increases after 2007. This is considered to be the result of the subprime mortgage crisis and the Lehman collapse. Before 2007, the changes of macroeconomic indicators are less important than those after 2007. In addition, in Figure 3, while retail sales and Michigan sentiment are more important before 2007 than after 2007, initial claims and unemployment rate are more important after 2007 than before 2007.

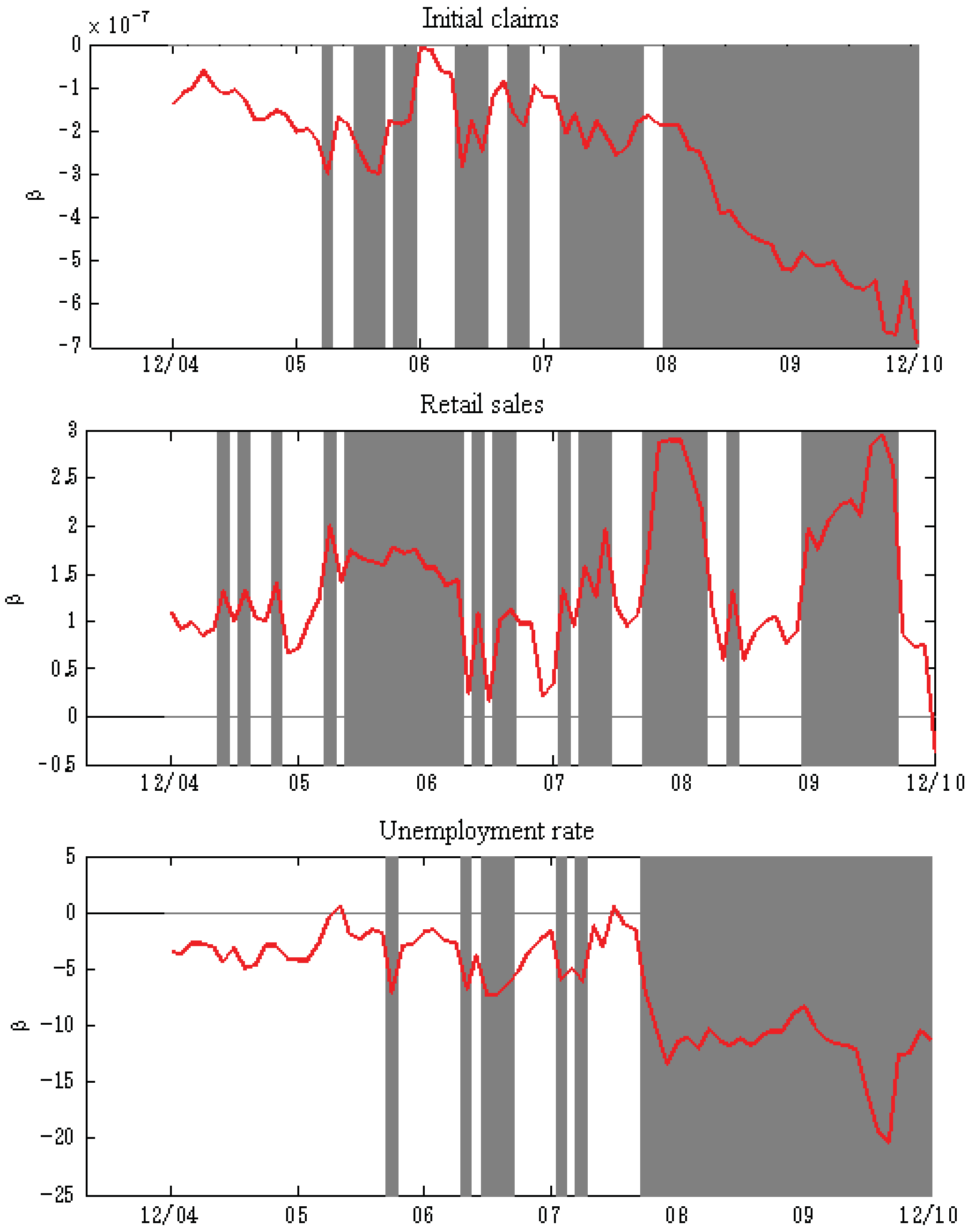


Fig. 4. Time-dependent effect of indicators (S&P 500 Future, T = 48 case)

These results suggest that investors paid less attention to macroeconomic indicators during the economic boom in the middle of the 2000s, which was modified after the shock of 2007. It is also suggested that investors paid more attention to the consumption index when the economy was booming, reflecting the large portion of consumption in the U.S. economy. On the other hand, after 2007, they started paying more attention to monetary policy and therefore employment indices. Although these hypotheses should be confirmed by more detailed discussion based on macroeconomic research, our method introduces a new way to extract information about market attention and economic status from market prices.

4. Prediction of return and risk

In this section, we show that prediction of return and risk in an out-of-sample period is possible based on our model, and the predicted values are reasonable. In addition, we show that the predetermined term introduced in equation (5) does not change the result significantly.

4.1. Out-of-sample predictions. Prediction of an out-of-sample return is possible by substituting $t = t_0 + 1$ into equation (7). Assuming $E[z_t^i] = 0$, the expected value of equation (7) is simply $E[r_t|t-1]$, which is not particularly useful. Instead, we consider substituting surprises predicted by investors into equation (7), as

$$\mu_{t_0+1}(\varepsilon) = E\left[r_{t_0+1}\middle|t_0\right] + \sum_{i\in I_{t_0}} \beta_{t_0}^i \varepsilon(z_{t_0+1}^i|t_0), \tag{6}$$

where $\varepsilon(z_{t_0+1}^i|t_0)$ is the predicted value of surprise $z_{t_0+1}^i$ by an investor based on the information available at time t_0. Then, $\mu_{t_0+1}(\varepsilon)$ corresponds to the predicted return under the prediction set $\left\{\varepsilon\left(z_{t_0+1}^i\middle|t_0\right)\right\}_{i\in I_{t_0}}$. Since market expectation can be interpreted as $\varepsilon(z_{t_0+1}^i|t_0) = E\left[z_{t+1}^i\right] = 0$, it is not our model but investors themselves that gives the method to obtain $\varepsilon(z_{t_0+1}^i|t_0)$. If a precise estimation of economic indicators is assumed to be available, then $\varepsilon(z_{t_0+1}^i|t_0) = z_{t_0+1}^i$.

Note that the method to know the set $\left\{z_{t_0+1}^i\right\}_i$ or $\left\{\varepsilon\left(z_{t_0+1}^i\middle|t_0\right)\right\}_{i\in I_{t_0}}$ is beyond our model. In the sense that our model does not give the method to obtain the values of necessary indicators, it is not a prediction model in itself. Instead, our model finds out important indicators related to returns. This has three advantages. First, it enables us to focus on prediction of important indicators. Second, it also enables us to relate stock risk with economic risk, as described in 4.2. Third, since these important indicators are considered to be paid attention by market participants, the information about important indicators can be used to judge market conditions.

The question may arise that prediction based on ex ante indicators is more desirable than prediction based on contemporaneous indicators. However, prediction based on ex ante indicators seems impossible for at least two reasons. First, if the effective market hypothesis holds, ex ante information is instantaneously reflected to stock price, theoretically. Second, some preceding studies empirically report its difficulty (e.g., Welch and Goyal, 2008), while others show that it is possible (e.g., Caompbell and Thompson, 2008).

The other question may arise that the prediction of economic indicator is also impossible as that of returns is. However, compared to the prediction of returns, in which all the information about the economy and the world is aggregated quickly, there exists room to improve the prediction of economic indicators.

In the case that important indicators can be predicted precisely, that is, if $\varepsilon\left(z_{t_0+1}^i\middle|t_0\right) = z_{t_0+1}^i$, then the correlation coefficient $\rho = \rho_0$ between r_t and $\mu_t = \mu_t(\varepsilon)$ measures how precisely these important indicators can predict the stock returns. Therefore, we define the square of ρ_0 as the explanatory power R_0^2 of out-of-sample period. This R_0^2 corresponds to the in-sample R^2, so we regard it as the measure of the validity of the model (8).

Figure 5 compares the realized return r_t with the predicted return μ_t. Their correlation coefficient ρ_0 varies from 0.2 to 0.5, corresponding to $R_0^2 = 0.04$ to 0.25, respectively. Table 4 compares the in-sample R^2 and out-of-sample R_0^2. Note that in-sample R^2 is given in analysis for each month while out-of-sample R_0^2 is given one value across the period in the analysis. Therefore, the average, maximum and minimum of in-sample R^2 is given in Table 4. While the explanatory power is less in the out-of-sample than the in-sample, our out-of-sample prediction gives a better result than preceding studies in the case of S&P Future and T = 48, S&P Future and T = 60, or Russell 3000 and T = 48.

Table 4. Comparison of R^2 between in-sample and out-of-sample periods

Period	T = 48			T = 60	T = 36
	S&P Future	Russel 3000	DJIA	S&P Future	S&P Future
In-sample					
Average	0.45	0.44	0.42	0.43	0.49
Maximum	0.81	0.81	0.81	0.72	0.90
Minimum	0.06	0.08	0.09	0.09	0.00
Out-of-sample	0.26	0.16	0.14	0.26	0.05

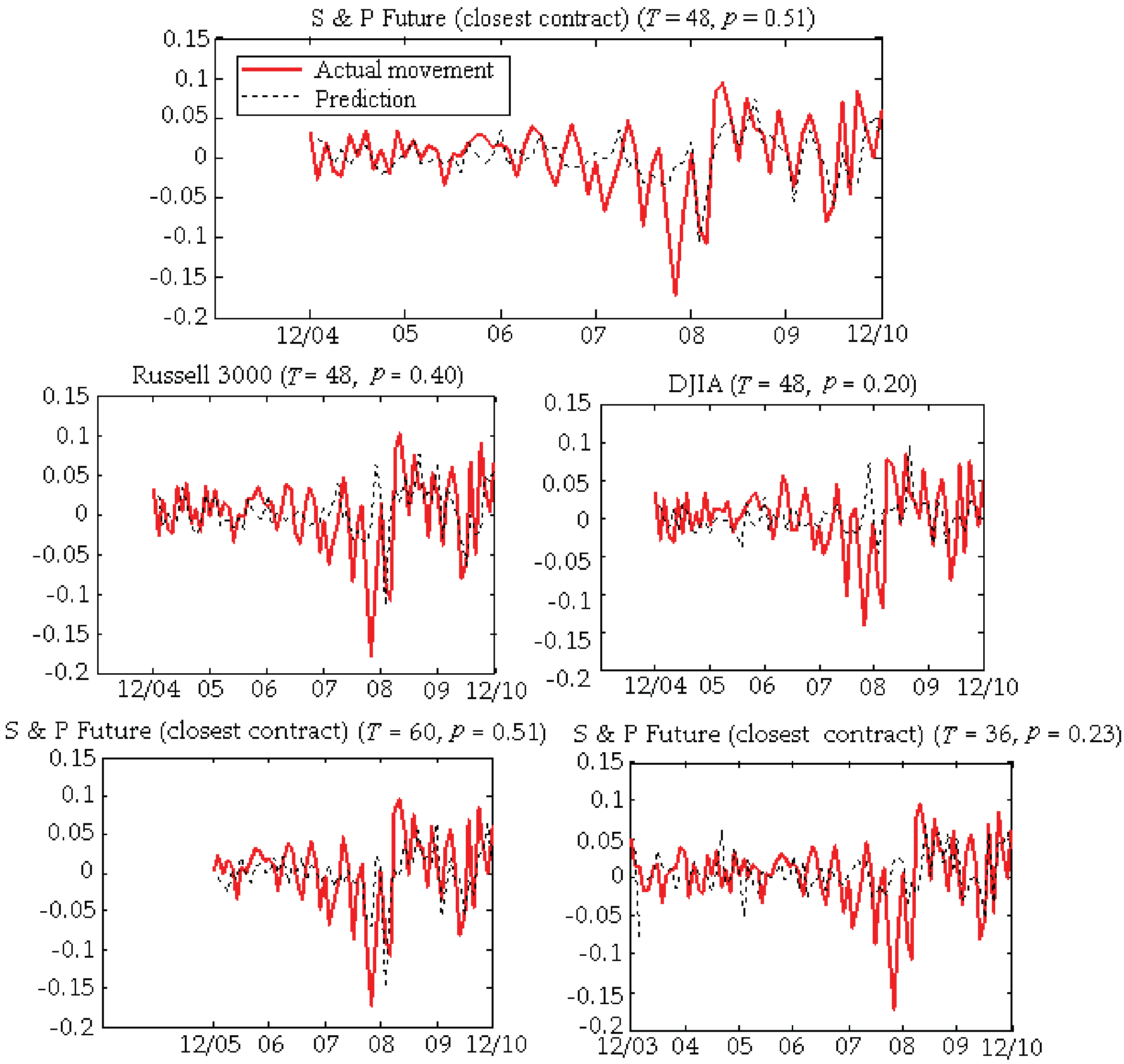


Fig. 5. Out-of-model prediction in rolling regression

4.2. Prediction of value at risk. In equation (7), the source of risk at time t_0 +1 is $\{z^i_{t_0+1}\}$ and ε_{t_0+1} Therefore, prediction of risk is also possible by the distribution of $\{z^i_{t_0+1}\}$ and ε_t into equation (7). This implies that the downside risk of stock returns is connected to the downside risk of economic indicators. We consider this application.

We assume $\{z^i_{t_0+1}\}$ and ε_{t_0+1} are independent and $\{z^i_{t_0+1}\}$ obey multivariate normal distribution $N(0, \mathrm{cov}\{z^i_{t_0}\})$. We apply ARMA(1,1)- GARCH(1,1) to time-series $\{\varepsilon_{t_0}\}$ and predict the distribution of ε_{t_0+1}. We numerically compute VaR values under these assumptions.

Figure 6 compares the actual return (actual movement) and our 5% VaR values obtained from this approach (VaR based on economic surprise). We also show the usual VaR, namely, VaR by applying the ARMA-GARCH model directly to the return series (usual VaR). Table 5 compares the ratio of the number of violations against VaR over the observation length in each model. Table 5 also show the ratio in two different periods, 2005-2007 and 2008-2010, for the case of T = 48.

In Figure 6 and Table 5, while both VaR values capture the tail risk of return, there are several differences between them. First, the number of violations during the entire period is generally less in our VaR model than in usual VaR, except the case of Russell 3000 in T = 48. Especially, during 2005-2007, in which the market is tranquil compared to 2008-2010 the ratio is restricted within 6%, our VaR gives violation ratio closer to 5%, which is expected. Second, after the sharp drop of actual return in October 2008, the variation of our VaR is more moderate than that of usual VaR. This property is preferable since an excessively large VaR poses the danger of overestimation of risk.

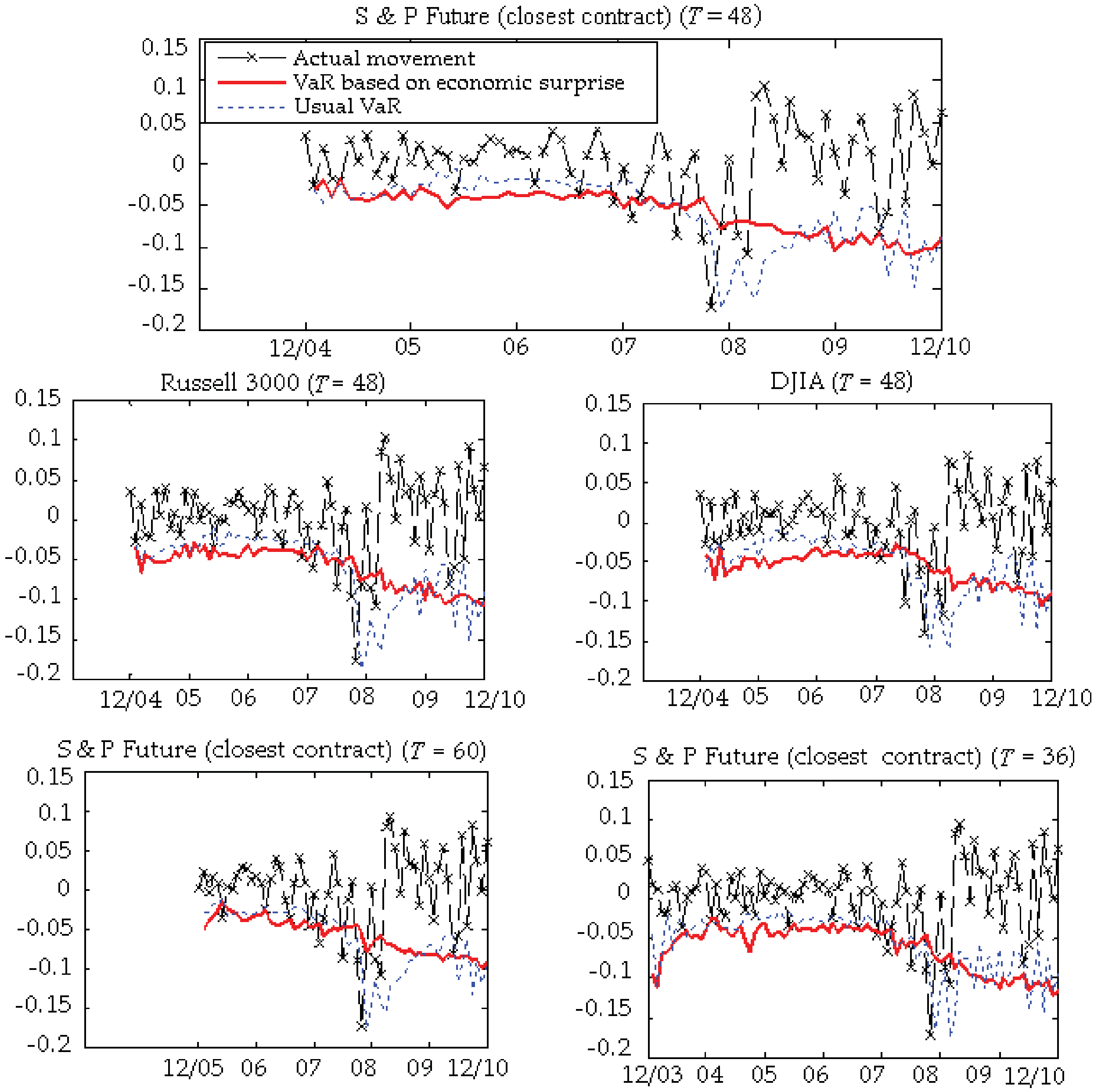


Fig. 6. VaR by ARMA-GARCH in rolling regression

Table 5. Violation ratio against VaR

	T = 48			T = 60	T = 36
	S&P Future	Russell 3000	DJIA	S&P Future	S&P Future
Entire period					
VaR based on economic surprise	0.111	0.125	0.097	0.117	0.131
Usual VaR	0.125	0.111	0.111	0.150	0.131
2005-2007					
VaR based on economic surprise	0.056	0.056	0.028		
Usual VaR	0.111	0.083	0.111		
2008-2010					
VaR based on economic surprise	0.167	0.194	0.167		
Usual VaR	0.139	0.139	0.111		

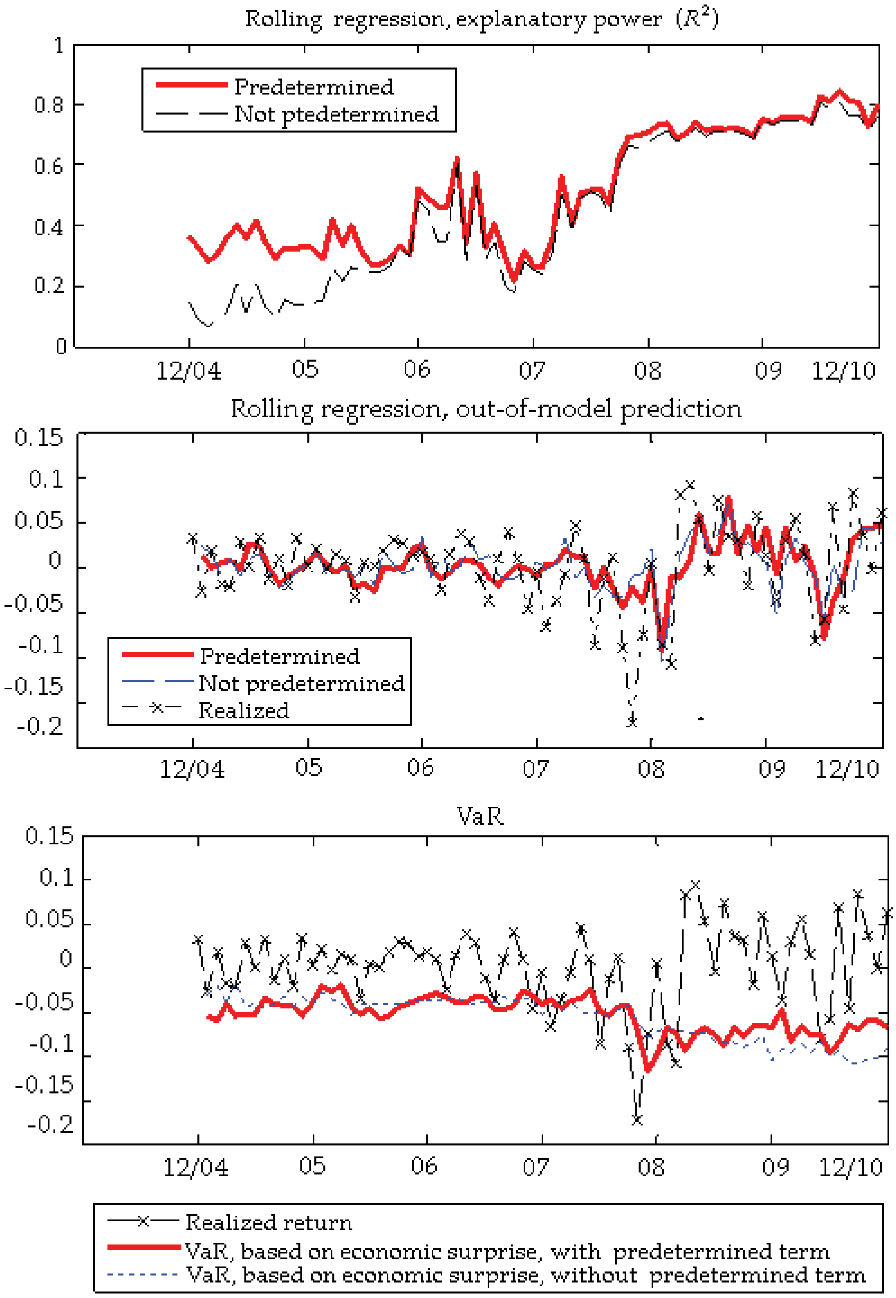


Fig. 7. Effect of predetermined return (S&P 500 Future, T = 48 case)

Note that it is also possible to consider extreme values of $z^i_{t_0+1}$ based on macroeconomic insights obtained from outside of our model. For example, we can consider scenarios in which many economic indicators become worse simultaneously, based on judgment derived from macroeconomic expertise.

4.3. Predetermined return. Let us consider the effect of predetermined return $E[r_t|t-1]$ given in (5). Since this equation is assumed to be deterministic, we simply use the entire period to determine the coefficients in equation (5). Then, we do the same robust, stepwise and rolling regressions for the residual series $r_t' = r_t - E[r_t|t-1]$.

Figure 7 compares explanatory power, out-of-model prediction and VaR based on equation (4) and equation (5). While explanatory power in the early period is slightly improved, there is no great difference between these two assumptions. Note that the explanatory power of equation (5) is around 0.12.

Conclusion

We introduce an approach to find important macroeconomic indicators whose news affect stock prices, based on robust, stepwise and rolling regression. Our approach is to find a time-dependent set of important indicators based on the fact that the effect of indicators varies over time. Based on our approach, we obtain higher explanatory powers than previous studies. In addition, we show that in-model variables and their coefficients reflect economic status. It should also be noted that our study covers a wider range of economic indicators than previous studies. We also show that prediction of returns and risk is possible using our model, and that this prediction is reasonable compared to the usual prediction in terms of VaR. Our model enables us to use economic indicators for the purpose of risk and return analysis.

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