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Technical Analysis, Business Cycle, and Stock Market Returns

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Abstract

This article provides nine profitable timing strategies based on the technical analysis of two specific macroeconomic variables (i.e., capacity utilization rate and unemployment rate). The success of our strategies is explained by the high persistence in the business cycle, which allows the two macroeconomic variables to anticipate future business conditions better than the S&P500 index. Furthermore, they create additional value in timing the market as the changes in stock prices reflect subsequent changes in business conditions.

JEL classification numbers: C53, E44, G14
Keywords: Technical analysis, Business-cycle forecasting, Market timing using real variables

1 Introduction

In a pioneering work, Levy (1966, pp.83) summarizes the technical theory as follows:
"1. Market value is determined solely by the interaction of supply and demand. 2. Supply and demand are governed by numerous factors, both rational and irrational. […]. 3. Disregarding minor fluctuations in the market, stock prices tend to move in trends, which persist for an appreciable length of time. 4. Changes in trend […] can be detected sooner or later in the action of the market itself."
Unfortunately, the theoretical foundation laid out by Levy (1966) has been subject to extensive critiques. Academic researchers tend to hold views that differ from those of the chartist. Particularly, advocates of the random walk hypothesis argue that the time series of stock returns has no reliable trends. The past price history of the stock market cannot provide any meaningful information that investors can utilize to achieve superior returns.

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Fama (1965, pp.59) makes an excellent point in this aspect: "If the random walk model is a valid description of reality, the work of the chartist, like that of astrologer, is of no real value in stock market analysis."

A natural question arises. Is it possible to accommodate the technical analysis with the random walk hypothesis? Indeed, is it possible to achieve a superior performance using technical analysis even if investors are rational? In this paper, we explore such a possibility by reexamining the vital link between the business cycle and stock market returns.[3]

Our paper is based on two well-known facts. First, it is well known that the long-term stock returns have to reflect the changes in business conditions, which affect the expected cash flows and returns, although the short-term stock returns may be affected by both rational and irrational factors. Second, with few exceptions, once a recession or expansion begins, it will last for a period of time.[4]

Given the vital link between the stock market and business conditions, the high persistence in the business cycle delivers us a novel idea for timing the stock market by identifying the turning points in business conditions. The success of a typical timing strategy may be illustrated by the following analysis. If we identify the trough and the peak at month $t_1 + m_1$ and $t_1 + k + m_1$, respectively, for an actual expansion period from month t_1 to $t_1 + k$, then we successfully predict the future business conditions of $k - m_1$ months consecutively from month $t_1 + m_1$ to $t_1 + k$. Under the assumption that the stock market leads the future business conditions by n months, we can successfully time the stock market by $k - m_1 – n$ months from $t_1 + m_1$ to $t_1 + k –n$. If k (the duration of persistence in business conditions) is substantially large and n (the time lead of stock market to the business conditions) and m_1 (the time lag of the identified turning points to the actual ones) are relatively small, then it is possible to form some investment strategies to successfully time the stock market over a substantially long sample period.

For example, the expansion spanning 1991-2001 began in March 1991 and ended in March 2001. Our representative model identifies the trough in July 1991 and the peak in May 2001, demonstrating that our model successfully predicts future business conditions of 117 months consecutively from July 1991 to March 2001. Under the empirical fact that the stock market leads future business conditions by 9 months, the model has superior predictability to the stock market over the 107 months from July 1991 to May 2001 and it can successfully time the stock market during these periods of time.

It should be noted that timing the market is not the sole purpose of this paper. We hope to reveal a new perspective on how stock returns are related to fundamentals and the business cycle. Moreover, the timing strategies' success or failure can demonstrate if the

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[3]Motivated by the widespread use of technical analysis in industry practice, academic researchers have been trying to test the performance of numerous technical trading rules against the market efficiency hypothesis. The majority of the studies in this area focus on analyzing the financial trading data without any reasonable attention assigned to the fundamentals. The discrepancy between technical analysis and fundamental analysis has been dramatically described as the difference between astrology and astronomy. In this article, we distinguish ourselves from the typical chartist by switching the attention from financial trading data to fundamentals. See Park and Irwin (2007) for a review on the profitability of technical trading rules.

[4]According to the statistics released by the National Bureau of Economic Research (NBER), there were 33 recessions and expansions of the U.S. economy during the period of 1854 to 2009. Each recession lasted an average of 16 months, and each expansion lasted an average of 42 months.

predictability of our technical analysis of the fundamentals has passed the test of the equity market.

We summarize our idea into three theoretical hypotheses by rewriting the technical theory in Levy (1966) as follows:

1). The stock market in the long term has to reflect the changes in business conditions, but it cannot precisely lead the future business conditions without a limit (i.e., n is nonnegative but relatively small).

2). Business conditions have a high degree of persistence. A(n) recession or expansion, once it begins, will last for a period of time (i.e., k is substantially large).

3). The persistence of the business conditions can be captured by some variables, and the turning points in the business conditions can be detected by these variables in a relatively timely way (i.e., m_1 and m_2 have small absolute value).

All the theoretical hypotheses listed above are independent of random walk hypothesis. The stock returns can reflect the fundamentals in a random-walk or nonrandom-walk way. Furthermore, distinguished from the typical practice of chartist, we do not forecast the trajectory of the market or the expected returns, which remains unknown throughout our nine timing strategies. Instead, we aim to find fundamental variables that can provide us useful information about when the economy is about to change a direction. Although the specific time when the market makes a turn is not necessarily coherent with the time the economy is about to turn, the two points should be closely related if the stock market reflects the changes in business conditions over a relatively long horizon. Therefore, the predictability of the turn of the market is accomplished to the extent that there is predictability of the turn of aggregate economic activities. The critical procedure for successfully implementing such an idea of predicting the stock returns is to identify some variables that can consistently capture the nature of business cycle persistence.

Our research methods also differ from the existing literature in terms of predicting the expected returns of equity. Most researchers in this area employ financial variables to forecast stock returns,[5] while applying an important hypothesis on how expectations may be formed. Because there is no direct data on expectations, the predictability of these financial variables is not necessarily driven by the expected future economic activity (Campbell and Diebold, 2009). Speculative elements may well be important at equilibrium; however, there are other objections as well. Ferson et al. (2003) document that many of the regressions used to predict stock returns in the literature may be spurious. Timmermann (2001), Rapach and Wohar (2006), Pesaran and Timmermann (2002) and Hartmann et al. (2008), among others, claim that the relationship between stock returns and predictor variables may be subject to structural breaks, which put the reliability of the predictive power of the related regression models into question. In this paper, we avoid these obstacles by exploring macroeconomic, not financial, variables in a nonparametric way to identify the economic turning points and time the stock market.

Dotsey and King (2005) and Alvarez-Lois (2006) provide some sophisticated models that use endogenous real variables in the form of variable capacity utilization, labor supply

[5]Noted examples can be found in Keim and Stambaugh (1986), Campbell (1987), Campbell and Shiller (1988), Fama and French (1988, 1989), among others. Furthermore, Chordia and Shivakumar (2002) and Avramov and Chordia (2006), among others, build a business cycle model with financial variables to resolve certain financial anomalies which are considered to contradict the market efficiency.

variability, and materials inputs to explain the high persistence in business conditions. They argue that "these real flexibilities considerably reduce the elasticity of the marginal cost with respect to output and thus lead to more gradual price adjustment, which in turn implies greater persistence in business conditions." Indeed, we find from the historical data of the U.S. economy (see Figure 1 and Table 1) that the variation of the unemployment rate is useful for determining if an expansion is about to end, and the variation of the capacity utilization rate is useful for determining if a recession is over.[6] Therefore, we use the information embodied in the unemployment rate to identify the peak point(s) of a business cycle, and we use the information embodied in the capacity utilization rate to identify the trough point(s). Our nine timing strategies are designed accordingly. A typical timing strategy of ours is to sell the S&P500 stock price index and buy the 1-month treasury bill once the peak point(s) have been identified and vice versa. With an initial investment of one dollar, the terminal values of these nine strategies—over the 40-year period from 1970 to 2009 with monthly compounding returns—range from 18.44 to 26.78. In contrast, the terminal value of the passive buy-and-hold strategy of the S&P500 stock price index over the same period is 12.11. The profitability of the nine strategies remains robust over different periods from 1980-2009, 1990-2009, and 2000-2009. Furthermore, our various tests, including the reality check for data snooping, have shown that our strategies have successfully timed the S&P500 index across different time periods.

2 Data Description and Economic Implication

The data employed in this article are obtained from the CRSP (Center for Research in Securities Prices) and the FRED (Federal Reserve Economic Data) at the Federal Reserve Bank of St. Louis. The capacity utilization rate and the civilian unemployment rate are monthly data. Because the unemployment rate and the capacity utilization rate are released on different dates by the Federal Reserve System and the U.S. Department of Labor, the monthly returns on our timing portfolios are calculated from the daily return data on the S&P 500 stock price index and the 1-month T-bill. To emphasize the issue of real-time data, we replace the revised capacity utilization rate data currently available on the FRB website with the real-time data from 1983 to 2009.[7] All of the empirical results are robust regarding whether we use the real-time data or not because the revisions on the capacity utilization rate and the unemployment rate are usually minor.

[6] The labor market performs very differently before and after a recession. This should be a key to understanding the causes of the business cycle.

[7] We thank senior economist Charlie Gilbert at the Federal Reserve Bank and economist Eleni Theodossiou at the Bureau of Labor Statistics for providing key information such as the release dates and some real-time data on the capacity utilization rate and the release dates on the unemployment rate, which enable us to implement our timing strategies in a more practical way.

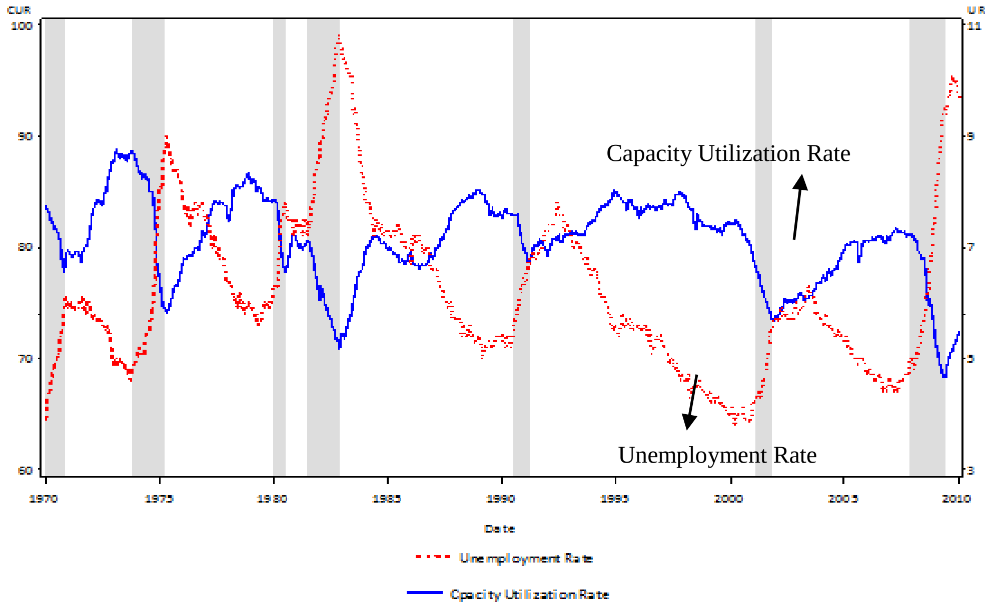

Figure 1: The Capacity Utilization Rate, the Unemployment Rate, and the Business Cycle Dates Identified by the NBER (Recessions are the Shaded Areas) from 1970-2009.

Figure 1 describes the capacity utilization and the unemployment rates against the business cycle reference dates identified by the NBER from 1970 to 2009. The shaded areas are the recessions announced by NBER. It shows that the capacity utilization rate starts to climb, with rare hesitations, when a recession is over. The unemployment rate goes down with very low volatility during an expansion until the expansion nears its end. The peak and trough dates of the unemployment rates and the capacity utilization rates of each recession since 1970 as well as the reference dates of the NBER are provided in Table 1. The analysis in Table 1 reveals that the unemployment rate reaches its bottom for each expansion earlier than the starting date of its subsequent recession, and the capacity utilization rate reaches its bottom for each recession just slightly later than the starting date of its subsequent recovery.

Table 1: Dates of Troughs and Peaks of the NBER Business Cycle, the Capacity Utilization Rate and the Unemployment Rate

Troughs Announced by NBER	**Troughs of CUR**	**Peaks of UR**
November-70	November-70	August-71
March-75	May-75	May-75
July-80	July-80	July-80
November-82	December-82	November-82
March-91	March-91	June-92
November-01	December-01	June-03
June-09	June-09	October-09
Peaks Announced by NBER	Peaks of CUR	Troughs of UR
November-73	February-73	October-73
January-80	December-78	May-79
July-81	December-80	December-80
July-90	January-89	March-89
March-01	December-94	April-00
December-07	April-07	October-06

Why does the U.S. economy behave in such a manner? We provide a simple model to explain such behavior. Let $F(\mu K, L)$ be the production function of the economy, where K is the stock of (business fixed and residential) capital, L is the units of labor, and μ is the capacity utilization rate. Consider a dynamic process under which the economy makes a turn from its expansion to contraction. There are three possible adjustments for the economy to make in the short-run: a). reduction in the stock of capital K; b). reduction in μ; and c). reduction in L. Because the capital is typically irreversible in the short run, the other two reductions in b) and c) are possible. To determine why firms are willing to reduce L in response to a contraction in production output, we write down the economic profit function $F(\mu K, L)-wL-(d(\mu)+r)\, p_k K$, where w is the real wage, r is the expected real interest rate, p_k is the real price of a unit capital, and $d(\mu)$ is the rate at which capital depreciates. Assume that $d'(\mu)>0$ and $d''(\mu)>0$. It is reasonable to assume that $d'(\mu)$ is close to zero for some low level μ, which may be considered as an endogenous variable at certain range (see Alvarez Lois (2006) and Dotsey and King (2006) for detail). Assume that w and r are rigid in the short run. Thus, firms choose μ such that $F'_1(\mu K,L)=d'(\mu)\, p_k$ and L such that $F'_2(\mu K,L)=w$. As the economy starts to contract, we will see a decline in μ and L at the same time, at least in the short-run. If a contraction lasts for a sustainable period, we will see sustainable reductions in μ and L. Note that at a high level μ, a decline in μ does not necessarily imply that the economy will start to contract. This implies that the unemployment rate is left as a reliable indicator for timing if an expansion is about to end. On the other hand, as the economy recovers from a recession, we expect that μ stays at a low level so that $d'(\mu)p_k$ is close to zero. Firms raise μ without a significant increase in the marginal costs (Alvarez Lois, 2006; Dotsey and King, 2006). Therefore, as the aggregate demand recovers by the end of a recession, we should be able to see a rise in μ. Note that there is no guarantee that the unemployment rate also makes a turn as the capacity utilization rate does, as the economy may well experience a “jobless recovery.” Note also that firms may not increase the stock of capital at the very early stages of a recovery. As a result, the capacity utilization rate provides a reliable variable to time when a recession is about to end. As the recovery continues, the economy will eventually start to generate jobs because a increase in μ cannot continue indefinitely without raising the cost $d'(\mu)p_k$. The analysis here is embarrassingly simple, although it may yet be far from the reality. Importantly, the model fits the empirical evidence in Figure 1 and Table 1 extremely well. Thus, we find that the unemployment rate provides valuable information regarding the time when an expansion is about to end, but it is less informative about the time when a recession is over. Interestingly, the capacity utilization rate is very informative about the time when a recession is over, but it is less informative about the time when an expansion is over. Therefore, we use the information embodied in the unemployment rate to identify the peak point(s) and the information embodied in the capacity utilization rate to identify the trough point(s). Our market timing strategies are based on this disparity of the two rates in their predictability of the business cycle.

3 Description of Timing Strategies

Forecasting future business conditions has been an exciting topic for researchers, see, among others, Harvey (1988, 1989), Stock and Waston (1989,1991), Estrella and Hardouvelis (1991), Friedman and Kuttner (1994), Chauvet (1998), Estrella and Mishkin (1996), Kim and Nelson (1998), Chauvet and Potter (2005), Chauvet and Hamilton (2006), Chauvet and Piger (2008) and Espinoza, Fornari and Lombardi (2011).[8] However, most of these studies employ financial variables and parametric methods to forecast future business conditions. They do not address if the predictability of their models is sufficient to successfully time the stock market and achieve superior returns. This article focuses on the use of macroeconomic variables and how the information withdrawn from them can be used to time both the trough and the peak of a business cycle. In the perspective of business cycle persistence, the predictability of business conditions is used to design the market timing strategies.

Specifically, we set up a non-parametric method to identify the peak or trough of a business cycle by following certain criteria.

Identify a Peak: Define DUR by

$$DUR(p) = UR_p - \min(UR_m, UR_{m+1}, \ldots, UR_p)$$

where UR_v is the observed unemployment rate at time v, v=m, m+1, …, p, and m is the month of the nearest maximal point of the unemployment rate curve. Let DUR be a given threshold value of the unemployment rate. Suppose that $DUR(p)>\overline{DUR}$ at time p* for the first time. If k is the month such that $UR_k = \min(UR_m, UR_{m+1}, \ldots, UR_{p^*})$ where $p^*\geq k\geq m$ then we say that the unemployment rate reaches its local bottom at month k. If the unemployment rate rises from its bottom at month k by more than the threshold value of $\overline{DUR}$, then the unemployment rate starts to reverse from a downward trend to an upward trend. We say that the economy is recessionary once the month k has been identified.

[8] See Hamilton (2010) for an excellent survey on most of these papers.

Identify a Trough: Define DCUR by

$$\mathrm{DCUR(t)} = \mathrm{CUR_t} - \min(\mathrm{CUR_n}, \mathrm{CUR_{n+1}}, \dots, \mathrm{CUR_t})$$

where CUR_v is the observed capacity utilization rate at time v, v=n, n+1, …, t, and n is the month of the nearest maximal point of the capacity utilization rate curve. Let $\overline{\mathrm{DCUR}}$ be a given threshold value of the capacity utilization rate. Suppose that DCUR(t)>$\overline{\mathrm{DCUR}}$ at time t* for the first time. If j is the month such that $\mathrm{CUR_j} = \min(\mathrm{CUR_n}, \mathrm{CUR_{n+1}}, \dots, \mathrm{CUR_{t*}})$, where t*≥j≥ n, then we can infer that the capacity utilization rate reaches its local bottom at month j. If the capacity utilization rate rises from its bottom at month j by more than the threshold value of $\overline{\mathrm{DCUR}}$, then the capacity utilization rate starts to return from a downward trend to an upward trend. We say that the economy is in recovery once the month j has been identified.

Timing Strategies: A market timing strategy is based on the S&P500 stock price index and the 1-month T-bill. Note that p* is the month when the economy is first identified to be recessionary after a proceeding expansion in a business cycle and t* is the month when the economy is first identified to be in recovery after a proceeding recession. A timing strategy operates as follows: Once the economy is identified to be recessionary at month p*, we sell all of our holdings in the S&P500 stock price index and invest our funds in the 1-month T-bill. We keep our positions in the T-bill until the economy is identified to be in recovery at month t*. Once the economy is identified to be in recovery at month t*, we sell all of our holdings in the 1-month T-bill and invest our funds in the S&P500 stock price index.
In this article, we study nine timing strategies by setting $\overline{\mathrm{DUR}}$ at 0.4%, 0.5% or 0.6% and $\overline{\mathrm{DCUR}}$ at 0.5%, 1% or 1.5%. It is important to note that these threshold values we choose for $\overline{\mathrm{DUR}}$ and $\overline{\mathrm{DCUR}}$ are not the result of data snooping in stock returns, as illustrated in subsequent sections. Values that are too small for $\overline{\mathrm{DUR}}$ or $\overline{\mathrm{DCUR}}$ would not capture the nature of the persistence in business cycle, while values that are too large for $\overline{\mathrm{DUR}}$ or $\overline{\mathrm{DCUR}}$ would not forecast the economic turning point in a relatively timely way. Both small and large values are excluded by the theoretical foundation that we build in the introduction.

4 Performances of Timing Strategies

Table 2 provides the terminal values of a one dollar initial investment over the 40-year period from 1970-2009 with monthly compounding returns on the nine timing strategies described in Section 3. The terminal value 18.44 of the strategy $\overline{\mathrm{DUR}} = 0.6\%$ and $\overline{\mathrm{DCUR}}$=0.5% is the least while the terminal value 26.78 of the strategy $\overline{\mathrm{DUR}} = 0.4\%$ and $\overline{\mathrm{DCUR}}$=1% is the greatest among all nine strategies. This is in comparison with the terminal value 12.11 of the passive buy-and-hold strategy of the S&P500 over the same period. A typical timing strategy $\overline{\mathrm{DUR}} = 0.5\%$ and $\overline{\mathrm{DCUR}}$=1% over the sample period of 1970-2009 has been given in Figure 2.

Table 2: Performance of the Timing Strategies over the Period of 1970-2009

$\overline{\mathrm{DUR}}$(%)	$\overline{\mathrm{DCUR}}$(%)=	**0.5**	**1**	**1.5**
0.4	Terminal Value	26.2182	26.7879	20.1895
	α	0.0018	0.0019	0.0013
	t-stat	1.8630	1.9017	1.3000
	β	0.6598	0.6519	0.5660
	$\beta_1-\beta_2$	0.1840	0.1910	0.0201
	F-stat	7.6954	8.1875	0.0830
0.5	Terminal Value	22.2773	24.0629	21.8286
	α	0.0015	0.0016	0.0014
	t-stat	1.5291	1.6991	1.4593
	β	0.6982	0.6953	0.6360
	$\beta_1-\beta_2$	0.1328	0.1346	0.0523
	F-stat	4.1681	4.2828	0.5924
0.6	Terminal Value	18.4440	19.9224	24.4911
	α	0.0011	0.0012	0.0017
	t-stat	1.1179	1.2896	1.7309
	β	0.7117	0.7089	0.6846
	$\beta_1-\beta_2$	0.1270	0.1288	0.1348
	F-stat	3.8987	4.0083	4.2469

Note: The three threshold values in $\overline{\mathrm{DUR}}$ ($\overline{\mathrm{DCUR}}$) are given in the first column (row).

This provides a combination of nine timing strategies. Both $\overline{\mathrm{DUR}}$ and $\overline{\mathrm{DCUR}}$ function as indicators to determine if the investment should be held in the S&P500 or in the one month T-bill. If the unemployment rate climbs up from its nearest bottom more than the threshold value $\overline{\mathrm{DUR}}$ for the first time, the investment strategy will be to buy and hold the T-bill. If the capacity utilization rate climbs up from its nearest bottom more than the threshold value $\overline{\mathrm{DCUR}}$ for the first time, the investment strategy will be to buy and hold the S&P500 index. The terminal value presented in the table is the terminal values of a $1 investment on a strategy over the 40-year period from 1970-2009 with monthly compounding returns The terminal value of the passive buy-and-hold S&P500 stock price index over the period of 1970-2009 is 12.11. α and β are estimated from regression 1: $\mathrm{R_p}-\mathrm{R_f}=\alpha+\beta(\mathrm{R_m}-\mathrm{R_f})+\varepsilon$, where $\mathrm{R_p}$, $\mathrm{R_m}$, and $\mathrm{R_f}$ are the returns on the timing strategy portfolio, the S&P500 stock price index and the risk-free asset, respectively β_1 and β_2 are estimated from regression 2: $\mathrm{R_p}-\mathrm{R_f}=\beta_0+\beta_1\max(\mathrm{R_m}-\mathrm{R_f},0)+\beta_2\min(\mathrm{R_m}-\mathrm{R_f},0)+\varepsilon$. $\max(\mathrm{R_m}-\mathrm{R_f},0)$ is the bull market risk premium, and $\min(\mathrm{R_m}-\mathrm{R_f},0)$ is the bear market risk premium. β_1 is the bull-market beta, and β_2 is the bear-market beta. The t-stat below α is to test the null hypothesis $\alpha=0$, and the F-stat below $\beta_1-\beta_2$ is to test the null hypothesis $\beta_1-\beta_2$=0.

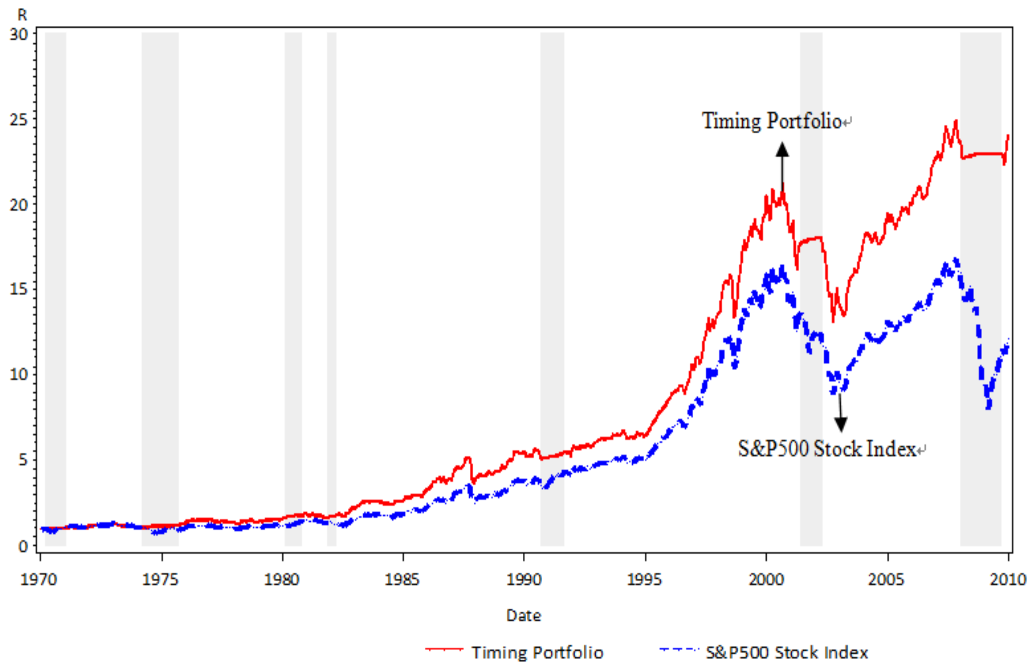

Figure 2: Performance of the Timing Strategy with $\overline{\text{DUR}}$=0.5 and $\overline{\text{DCUR}}$=1 over 1970-2009.

Note: We sell the S&P stock index and then buy and hold the 1-month T-bill once $\overline{\text{DUR}}$>0.5 until $\overline{\text{DCUR}}$>1, after which we sell the 1-month T-bill and buy and hold the S&P stock price index until $\overline{\text{DUR}}$>0.5 of the next business cycle. Shaded areas are the recessions identified by the NBER. The R-axis is the terminal value of a $1 investment of the timing strategy with $\overline{\text{DUR}}$=0.5 and $\overline{\text{DCUR}}$=1 over the 40-year period from 1970-2009 with monthly compounding returns.

Next, we use the market model (Regression 1),

$$R_p - R_f = \alpha + \beta(R_m - R_f) + \varepsilon$$

and the Henriksson-Merton model (Regression 2),

$$R_p - R_f = \beta_0 + \beta_1 \max(R_m - R_f, 0) + \beta_2 \min(R_m - R_f, 0) + \varepsilon$$

to test how successful our strategies are in timing the stock returns, where R_p, R_m and R_f are the returns on the timing strategy portfolio, the stock market portfolio and the risk-free asset, respectively. In Regression 2, $\max(R_m - R_f, 0)$ is the bull market risk premium and $\min(R_m - R_f, 0)$ is the bear market risk premium. β_1 is the bull-market beta and β_2 is the bear-market beta. The estimates α and β in Regression 1 show whether a timing strategy can gain positive market risk adjusted returns. A successful market-timing in Regression 2 requires β_1-β_2>0.[9]

Table 2 shows that in Regression 1, all nine strategies have positive excess returns adjusted by market risk, and the monthly returns on these strategies are less volatile than the market index of the S&P500 because the estimates of β are all significantly less than 1. In Regression 2, all nine strategies have strictly positive β_1-β_2, which means that these strategies have successfully timed the market in the sense of Henriksson and Merton (1981). To illustrate how sensitive our nine timing strategies are to the initial investment dates, we also provide the results on the nine strategies with different investment periods in Table 3. The results show that our nine strategies are quite robust to different choices of the initial investment dates. They outperform the passive buy-and-hold strategy of the S&P500 indices from 1970-2009, 1980-2009, 1990-2009, and 2000-2009.

Table 3: Performance of the Timing Strategies Over the Subsample Periods

Investment Periods		1980-2009			1990-2009			2000-2009		
Terminal value of investing $1 of the buy-and-hold S&P 500 stock price index		10.33			3.16			0.76		
$\overline{DUR}$(%)	$\overline{DCUR}$(%)=	0.5	1	1.5	0.5	1	1.5	0.5	1	1.5
0.4	Terminal Value	17.93	17.50	13.19	5.33	5.53	6.66	1.22	1.26	1.59
	α	0.002	0.002	0.002	0.003	0.003	0.004	0.002	0.002	0.003
	t-stat	1.995	1.93	1.31	2.12	2.22	2.81	0.69	0.83	1.64
	β	0.72	0.71	0.60	0.67	0.67	0.61	0.46	0.46	0.40
	$\beta_1-\beta_2$	0.27	0.27	0.03	0.32	0.34	0.35	0.27	0.28	0.37
	F-stat	13.90	14.44	0.18	11.91	13.37	13.46	3.53	3.86	7.42
0.5	Terminal Value	15.00	15.47	14.04	4.20	4.33	5.47	1.13	1.17	1.47
	α	0.002	0.002	0.003	0.003	0.002	0.003	0.001	0.001	0.003
	t-stat	1.51	1.60	1.37	1.32	1.43	2.17	0.54	0.68	1.44
	β	0.76	0.76	0.68	0.68	0.68	0.64	0.53	0.52	0.47
	$\beta_1-\beta_2$	0.22	0.22	0.10	0.24	0.24	0.31	0.24	0.25	0.35
	F-stat	10.14	10.33	1.87	6.26	6.45	10.60	2.76	3.03	5.91
0.6	Terminal Value	12.42	12.81	15.75	4.06	4.19	5.29	1.09	1.13	1.42
	α	0.001	0.001	0.002	0.002	0.002	0.003	0.001	0.001	0.003
	t-stat	0.97	1.06	1.65	1.21	1.31	2.06	0.44	0.58	1.34
	β	0.78	0.78	0.75	0.69	0.69	0.65	0.54	0.54	0.48
	$\beta_1-\beta_2$	0.213	0.214	0.220	0.239	0.241	0.315	0.257	0.265	0.361
	F-stat	10.03	10.22	9.97	6.54	6.74	10.94	3.11	3.40	6.37

Note: This table shows the performance of the nine timing strategies described in Table 2 over the periods from 1980-2009, 1990-2009, and 2000-2009. $\overline{DUR}$, $\overline{DCUR}$, α, $\beta, \beta_1-\beta_2$ and the related statistical test variables in this table are described in Table 2. The terminal value of the passive buy-and-hold S&P500 stock price index over the same period is 12.11.

[9]See Henriksson and Merton (1981).

4.1 Tests on the Theoretical Hypotheses

In this section, we will focus on the timing strategy with $\overline{\text{DUR}}$=0.5 and $\overline{\text{DCUR}}$=1 to test the theoretical hypotheses we summarize in the introduction. Since the persistence in business conditions is a stylized fact about the macro-economy, we will mainly provide empirical evidence on the other two theoretical hypotheses.

1). The time lead of stock market to the business conditions (n is nonnegative but relatively small).

We set up a Probit model as follows:

$$\Pr(I_t = 1) = F(\beta_0 + \beta_1 R_{t-1} + \beta_2 R_{t-2} + \beta_2 R_{t-3} + \cdots + \beta_2 R_{t-m})$$

where Pr is the probability of the event I_t =1. I_t is a binominal variable that equals 1 if the economy at time t is in a recession and equals 0 otherwise. F is the cumulative normal distribution function, and $R_{t-1}, R_{t-2}, R_{t-3}, \ldots, R_{t-m}$ are the investment returns on the S&P500 stock price index at months t-1, t-2, t-3,…, t-m, respectively. If the stock price leads the future business conditions by m months, then we should achieve estimates of $\beta_{1,} \beta_2, \beta_3, \ldots, \beta_m,$ which are significant with the correct signs.

Table 4 presents the empirical result of the Probit model using the NBER business cycle reference dates and the monthly S&P500 stock price index over the sample period of 1970 to 2009. As shown in Table 4, all the returns on the S&P500 stock price index at month from t-1 to t-9 have predictive power, at significance level of 5%, on the future of economic conditions at time t. In contrast, the returns on the S&P500 stock price index at time from t-10 to t-13 have lost their predictive power on the future of economic conditions at time t. The above empirical results show that the stock market or the average investor, may lead for some time (approximately 9 months in Table 4), but it cannot lead without a limit (n is nonnegative but relatively small) .

Table 4: The Time Lead of Stock Market to the Business Conditions

	R_{t-1}	R_{t-2}	R_{t-3}	R_{t-4}	R_{t-5}	R_{t-6}	R_{t-7}	R_{t-8}	R_{t-9}	R_{t-10}	R_{t-11}	R_{t-12}	R_{t-13}
Parameters β_i	-5.06	-8.25	-8.07	-10.99	-9.62	-9.11	-9.37	-8.24	-5.42	-3.83	-3.75	-2.91	0.99
Wald Chi-squared	6.48	16.25	15.77	28.02	22.57	19.52	18.76	14.32	6.36	3.15	2.97	1.62	0.18
p-value	0.01	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.08	0.09	0.20	0.67

Note: This table presents the parameters and related statistical test variables estimated from the following model: $\Pr(I_t = 1) = F(\beta_0 + \beta_1 R_{t-1} + \beta_2 R_{t-2} + \beta_2 R_{t-3} + \cdots + \beta_2 R_{t-m})$, where Pr is the probability of the event $I_t = 1$, I_t is a binominal variable that equals 1 if the economy at time t is in recession and equals 0 if otherwise, F is the cumulative normal distribution function, $R_{t-1}, R_{t-2}, R_{t-3}, \ldots, R_{t-m}$ are the returns on the S&P stock price index at the months t-1, t-2, t-3,…, t-m, respectively. If the stock price leads the macroeconomic economy by the m months, then we can obtain significant estimates of β_1, $\beta_2, \beta_3, \ldots, \beta_m$. Wald Chi-squared and related p-value are used to test the null hypothesis that the estimated parameters equal 0. The larger the Wald Chi-squared or the lower the p-value, the less likely the null hypothesis is to be true. The stock market leads the economy, with limited predictive power (approximately 9 months).

2). The time lag of the identified turning points to the actual ones (m1 and m2 are relatively small).

Table 5 presents the predicted business cycle dates using the timing strategy with $\overline{\mathrm{DUR}}$=0.5 and $\overline{\mathrm{DCUR}}$=1. The strategy has successfully forecasted 58 out of 83 months of recession and 366 out of 391 months of expansion. Although most of the predicted peaks or troughs come slightly later than those reference dates identified by the NBER, the two macroeconomic variables well capture the nature of persistence in business conditions. Furthermore, they predict the turning points in a relatively timely way. For example, the timing model with $\overline{\mathrm{DUR}}$=0.5 and

Table 5: Business Cycle Dates Forecasted by the Timing Strategy with $\overline{\mathrm{DUR}}$=0.5 and $\overline{\mathrm{DCUR}}$=1

	Predicted	NBER	Announcement	P-N	A-N	A-P
		Panel A				
Peaks	March-70	December-69	-	3	-	-
	March-74	November-73	-	4	-	-
	February-80	January-80	June-80	1	5	4
	November-81	July-81	January-82	4	6	2
	September-90	July-90	April-91	2	9	7
	May-01	March-01	November-01	2	8	6
	January-08	December-07	December-08	1	12	11
		Average		2	8	6
		Panel B				
Troughs	January-71	November-70	-	2	-	
	September-75	March-75	-	6	-	
	October-80	July-80	July-81	3	12	9
	March-82	November-82	July-83	8	8	0
	July-91	March-91	December-92	4	20	16
	June-02	November-01	July-03	7	19	12
	September-09	June-09	September-10	3	9	6
		Average		5	14	9

Note: This table presents the business cycle dates of peaks and troughs forecasted by the timing strategy described in Figure 2, and they are compared with the reference dates identified by the NBER and the time when the NBER made the announcement. Before 1980, the NBER had no formal announcement on the business cycle dates. P-N is the difference of months of each peak (Panel A) or trough (Panel B) between the forecasted date of the timing strategy and the reference date identified by the NBER. A-N is the difference of months of each peak (Panel A) or trough (Panel B) between the announcement and the reference date of the NBER. A-P is the difference of months of each peak (Panel A) or trough (Panel B) between the announcement and forecasted date of the timing strategy. One exception is the peak in November 1982, which is identified by the timing strategy 8 months earlier in March 1982. All of the other toughs and peaks identified by our strategy are slightly later than the actual business cycle dates.

$\overline{\mathrm{DCUR}}$=1 identifies the trough and peak in July 1991 and May 2001, respectively, for the actual expansion period of March 1991 to March 2001. Although the predicted economic turning points are 4 months and 2 months later than the actual dates announced by NBER, our model still successfully predicts the future business conditions of 117 consecutive months from July 1991 to March 2001. Because the stock market leads the future business conditions for 9 months, the model has superior predictability relative to the stock market over the 107 months from July 1991 to May 2001. In overall, the average time lag of the identified troughs and peaks to the reference date announced by the NBER are 5 months and 2 months, respectively. Both of them are small relative to the duration of the business cycle. Taking into account the above empirical facts, it is not surprising for our models to successfully time the stock market and achieve superior returns over the sample period of 1979 to 2009.

Because both bad and good news are mixed in the stock price near the end of an expansion or a recession, the stock market may turn earlier than the business conditions. Consequently, the first hypothesis on the link between the stock market and business conditions may be violated during these periods. Although the length of these periods is short relative to the whole sample period, the performance of the timing strategies will be negatively impacted in a certain way. Indeed, as illustrated in Figure 3, if we could switch our investment 9 months earlier than the identified turning points in business conditions, the timing strategy with $\overline{\text{DUR}}$=0.5 and $\overline{\text{DCUR}}$=1 would achieve a much higher terminal value of almost \$70, in contrast to that reported in Table 2 and Figure 2.

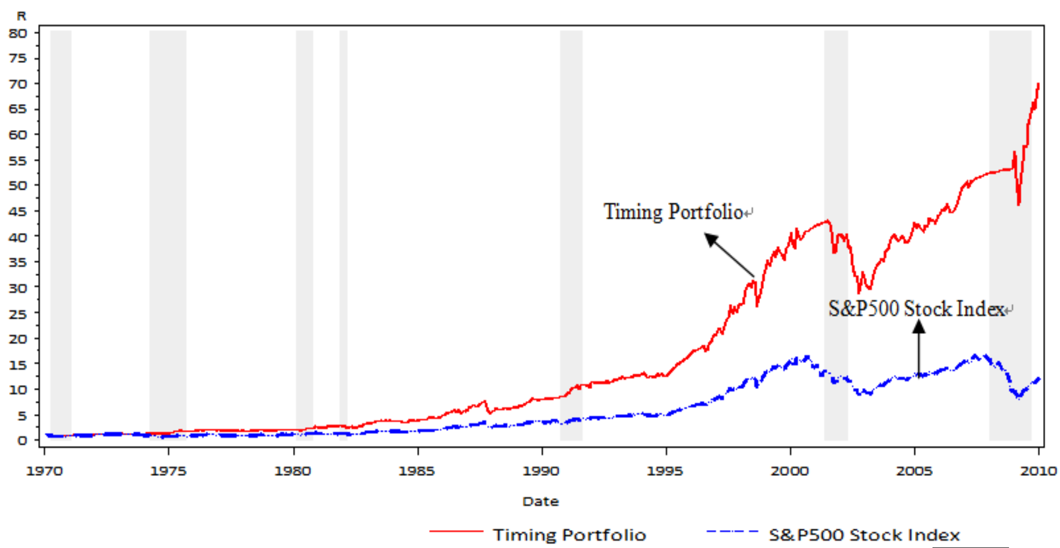

Figure 3: Performance of the Improved Timing Strategy with $\overline{\text{DUR}}$=0.5 and $\overline{\text{DCUR}}$=1 over 1970-2009.

Note: The R-axis is the terminal value of a \$1 investment on the timing strategy with $\overline{\text{DUR}}$=0.5 and $\overline{\text{DCUR}}$=1 over the 40-year period with monthly compounding returns in which we could switch our investment 9 months earlier than the identified turning points in business conditions.

Finally, the timing model with $\overline{\text{DUR}}$=0.5 and $\overline{\text{DCUR}}$=1 predicts the dates of peaks on average six months earlier than the time when NBER made its announcement since 1980 and the dates of troughs on average nine months earlier (Table 5). The NBER withholds an announcement until there will be little doubt regarding a peak or trough of the business cycle. Additionally, the committee considers multiple factors in making its decision, any one of which would delay an announcement. The NBER approach has its advantage over ours: the longer it delays its announcement, the more reliable its announcement should be.

The disadvantage of such an approach is a long delay, which makes it less valuable for timing the market. The multiple factor approach also shows how little we have known about timing the business cycle. Our two variables approach does not imply that other factors are not important for timing the business cycle. For example, the term structure remains a successful and robust prediction of recessions over the years (see, e.g., Harvey, 1988, 1989; Estrella and Hardouvelis, 1991). Nevertheless, our empirical and theoretical studies show that these two macroeconomic variables are important and reliable to establish the timing of the business cycle.

4.2 Reality Check for Data Snooping

Although we have summarized the theoretical hypotheses for the technical analysis of fundamentals and provided some supporting evidence in the above, our analysis may still suffer from the critiques of data snooping in stock returns. Some researchers may suggest that the superior performances of our timing models just accommodate the historical returns by chance. In this section, we employ the Reality Check, proposed by White (2000) and Sullivan, Timmermann and White (1999), to document that the performances of our timing rules are not result of data snooping in stock returns.[10]

Following Neuhierl and Schluschey (2011), we define the performance statistic for the k-th timing rule as

$$\bar{f}_k = \frac{1}{n}\sum_{t=1}^{n} f_{k,t+1}$$

where n is the number of trading days over the sample period of January 1970 to December 2009; $f_{k,t+1}$ is the observed performance measure for the k-th timing rule at time t+1. Particularly, the performance measure of mean return for the timing rule k at time t+1 can be calculated as follows:

$$f_{k,t+1} = \mathrm{In}\big(1 + RM_{t+1}X_{k,t+1} + RF_{t+1}(1 - X_{k,t+1})\big) - \mathrm{In}(1 + RM_{t+1}X_0)$$

1-month T-bill at time t+1. $X_{k,t+1}$ is the "timing function" that equals 1 for a forecasted expansion at time t+1 and equals 0 for a forecasted recession at time t+1. X_0 represents the buy-and-hold strategy of the S&P500 stock price index, which equals 1 at all times. Formally, the null hypothesis is:

$$H_0 = \max_{k=1,2,\ldots,9}\{E(f_k)\} \leq 0$$

If we can find one timing rule that achieve performance superior to the buy-and-hold strategy of the S&P500 stock price index, then the null hypothesis should be rejected at a significant level.

As shown in White (2000), Sullivan, Timmermann and White (2000) and Neuhierl and

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[8]Neuhierl and Schluschey (2011) employ White's Reality Check for market-timing rules, and they find that market-timing rules do not remain significantly profitable after correcting for data snooping.

Schluschey (2011), the null hypothesis can be evaluated by applying the stationary bootstrap of Politis and Romano (1994) to resample the observed return series for sufficient times.[11] We denote the resampled performance statistics for the k-th timing rule by $\overline{f^*}_{k,j}$, where j=1,2,…, 500 is the j-th repetition of the bootstrap. Then, we compute the following statistics for the nine timing rules proposed in this article.[12]

$$V_k = \max_{k=1,2\ldots,9}\{\sqrt{n}\bar{f}_k\}$$
$$V^*_{k,j} = \max_{k=1,2\ldots,9}\{\sqrt{n}(\overline{f^*}_{k,j} - \bar{f}_k)\} \qquad j = 1,2,\ldots,500$$

By comparing V_k to the quantiles of $V^*_{k,j}$, we can obtain the White's Reality Check p-value for the null hypothesis that the best timing model cannot outperform the buy-and-hold strategy of the S&P 500 Stock Price Index.[13] The empirical results are reported in Table 6.

As shown in Table 6, all the White's Reality Check p-values for the mean return criterion are different from zero at a significant level of 5%, and all the White's Reality Check p-values for the Sharpe Ratio criterion are different from zero at a significant level of 1%, both of which definitely suggest that the superior performances of the timing rules proposed in this article are not the result of data snooping in historical returns. Notice that the stationary bootstrap depends on the smoothing parameter q to determine the mean length of the blocks (1/q) drawn from the original return series. A large value of q can be chosen for the time series with little dependence, while a smaller value of q can be chosen for the time series with a larger dependence. Because the return data we use are at the daily frequency, q that equals 0.1 is appropriate for our experiment (Sullivan, Timmermann and White, 1999). However, the empirical results are not sensitive to the variation in the values of q.

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[9]See the Appendix C in Sullivan, Timmermann and White (2000) for a detailed description of the stationary bootstrap of Politis and Romano (1994). We follow exactly the three steps described there to generate the pseudo-time series of returns.

[10]Because we do not actually document if other technical rules such as moving average meet the theoretical hypotheses summarized in the introduction, we limit the universe of technical trading rules to the nine timing rules proposed in this article.

[11]The above procedures can be easily revised to accommodate the performance statistics of Sharpe Ratio. See Sullivan, Timmermann and White (1999) for the details.

Table 6: White's Reality Check p-values

Smoothing Parameter	q=0.01		q=0.1		q=0.5	
Performance Criterion	Mean Return	Sharp Ratio	Mean Return	Sharp Ratio	Mean Return	Sharp Ratio
1970-2009	0.004	0.000	0.006	0.000	0.000	0.000
1980-2009	0.030	0.000	0.040	0.006	0.050	0.000
1990-2009	0.000	0.000	0.004	0.000	0.000	0.000
2000-2009	0.000	0.000	0.002	0.000	0.000	0.000

Note: This table presents the White's Reality Check p-value for several sample period and performance criterion combinations, along with three different values of the smoothing parameter q (i.e., 0.01, 0.1 and 0.5). The stationary bootstrap depends on the smoothing parameter q to determine the mean length of the blocks (1/q) drawn from the original return series. A large value of q can be chosen for a time series with little dependence, while a smaller value of q can be chosen for a time series with larger dependence. Because the return data we use are at the daily frequency, q that equals 0.1 is appropriate for our experiment (Sullivan, Timmermann and White, 1999).

5 Conclusions

This paper presents nine timing strategies that have successfully timed the S&P500 stock price index over the 1970-2009 period based on the technical analysis of two specific macroeconomic variables (i.e., capacity utilization rate and unemployment rate). The significance of this paper lies in at least three fronts. First, the technical analysis is not necessarily conflictive with fundamental analysis or the random walk hypothesis. All of the technical analysis of the fundamentals that meet the theoretical hypotheses we summarize in the introduction part should be capable of achieving a performance superior to the buy-and-hold strategy of a market index. Future research can continue to test the profitability of other technical rules such as moving average, under the guidance of our theoretical hypotheses. Second, investors should not ignore the information embodied in the macroeconomic variables when they make their investment decisions. Indeed, this article provides successful examples on how to time the stock market based on the stylized fact of the persistence in the business cycle. It is of vital interest to find out other ways in which the stock market and macroeconomic conditions are related and examine if the relationship can be transformed into profitable investment strategies. Third, policy makers can follow our footprints to identify the business cycle in a timelier manner than the announcements of the NBER. We predict the dates of peaks on average six months earlier than the time when NBER made its announcement since 1980 and the dates of troughs on average nine months earlier. The value of such timing should not be underestimated for conducting the monetary and fiscal policy.

ACKNOWLEDGEMENTS: This paper supersedes the one entitled "Timing Stock Market Using Real Variables". We thank two anonymous referees for their helpful and positive comments that lead to this publication. Most financial journals take it as a norm that the passive buy-and-hold strategy always wins. But, if that is the case, there is no point at all of doing investment related analyses. Clearly, the practice says otherwise.

References

[1] Alvarez-Lois, P. P., Endogenous capacity utilization and macroeconomic persistence, *Journal of Monetary Economics* **53**, 2006, 2213-2237.

[2] Avramov, D. and T. Chordia, Asset pricing models and financial market anomalies, *Review of Financial Studies* **19**, 2006, 1001-1040.

[3] Campbell, J.Y., Stock returns and the term structure, *Journal of Financial Economics* **18**, 1987, 373 -399.

[4] Campbell, J.Y. and R. J. Shiller, The dividend–price ratio and expectations of future dividends and discount factors, *Review of Financial Studies* **1**, 1988, 195–227.

[5] Campbell, S.D. and F.X. Diebold, Stock returns and expected business conditions: half a century of direct evidence, *Journal of Business and Economic Statistics*, 2009, 266-278.

[6] Chauvet, M., An economic characterization of business cycle dynamics with factor structure and regime switches, *International Economic Review* **39**, 1998, 969-996.

[7] Chauvet, M. and S. Potter, Forecasting recessions using the yield curve, *Journal of Forecasting* **24**, 2005, 77-103.

[8] Chauvet, M. and J.D. Hamilton, "Dating business cycle turning points", in Costas M., P. Rothman, and D. V. Dijk, eds.: Nonlinear Time Series Analysis of Business Cycles, 2006, Elsevier, Amsterdam.

[9] Chauvet, M. and J.Piger, A comparison of the real-time performance of business cycle dating methods, *Journal of Business Economics and Statistics* **26**, 2008, 42-49.

[10] Chordia, T. and L. Shivakumar, Momentum, business cycle and time-varying expected returns, *Journal of Finance* **57**, 2002, 985-1019.

[11] Dotsey, M. and R.G. King, Pricing, production, and persistence, J*ournal of the European Economic Association* **4**, 2006, 893-928.

[12] Espinoza, R., F. Fornari and M. J. Lombardi, The role of financial variables in predicting economic activity, *Journal of Forecasting* **31**(1), 2012, 15–46.

[13] Estrella, A. and F.S. Mishkin, 1996, Predicting U.S. recessions: financial variable as leading indicators, *The Review of Economics and Statistics* **80**, 1996, 45-61.

[14] Estrella, A. and G.A. Hardouvelis, 1991, The term structure as a predictor of real economic activity, *Journal of Finance* **46**, 1991, 555-576.

[15] Fama, E.F., Random walks in stock market prices, *Financial Analyst Journal* (September-October), 1965, 55-59.

[16] Fama, E.F. and K.R. French, 1988, Permanent and temporary components of stock prices, *Journal of Political Economy* **96**, 1988, 246-273.

[17] Fama, E.F. and K.R. French, Business conditions and expected returns on stocks and Bonds, *Journal of Financial Economics* **25**, 1989, 23-49.

[18] Ferson, W. E., S. Sarkissian and T.T. Simin, Spurious regressions in Financial Economics, *Journal of Finance* **58**, 2003, 1393-1414.

[19] Friedman, B.M. and K.N. Kuttner, Why does the paper-bill spread predict real economic activity, 1994, NBER Working Paper 3879.

[20] Hamilton, J.D., Calling recessions in real time, *International Journal of Forecasting* **27**, 2010, 1006-1026.

[21] Hartmann, D., B. Kempa, and C. Pierdzioch, Economic and financial crises and the predictability of U.S. stock returns, *Journal of Empirical Finance* **15**, 2008, 468-480.

[22] Harvey, C.R., The Real Term Structure and Consumption Growth, *Journal of Financial Economics* **22**, 1988, 305-334.

[23] Harvey, C.R., Forecasting Economic Growth with the Bond and Stock Markets, *Financial Analysts Journal* (**September-October**), 1989, 38-45.

[24] Henriksson, R.D. and R. C. Merton, On the market timing and investment performance of managed portfolios II - statistical procedures for evaluating forecasting skills, *Journal of Business* **54**, 1981, 513-533.

[25] Keim, D.B. and R.F. Stambaugh, Predicting returns in the stock and bond markets, *Journal of Financial Economics* **17**, 1986, 357-390.

[26] Kim, C., and C.R. Nelson, Business cycle turning points, a new coincident index, and tests of duration dependence based on a dynamic factor model with regime-switching, *Review of Economics and Statistics* **80**, 1998, 188-201.

[27] Levy, R.A., Conceptual foundations of technical analysis, *Financial Analyst Journal* (**June-August**), 1966, 83-89.

[28] Neuhierl, A. and B. Schlussche, Data snooping and market-timing rule performance, *Journal of Financial Econometrics*, 2011, forthcoming.

[29] Park, C. and S.H. Irwin, What do we know about the profitability of technical analysis, *Journal of Economic Surveys* **21**, 2007, 786-826.

[30] Pesaran, M. H. and A. Timmermann, Market timing and return prediction under model instability, Journal of Empirical Finance 9, 2002, 495-510.

[31] Politis, D. and J. Romano, The Stationary Bootstrap, *Journal of The American Statistical Association* **89**, 1994, 1303-1313.

[32] Rapach, D.E. and M. E. Wohar, Structural breaks and predictive regressions models of aggregate U.S. stock returns, *Journal of Financial Econometrics* **4**, 2006, 238-274.

[33] Stock, J.H., and M.W. Watson, New indexes of coincident and leading economic indicators, in Blanchard, O. J. and F. Stanley, eds.: NBER Macroeconomics Annual, 1989, MIT Press, Cambridge, MA.

[34] Stock, J.H. and M.W. Watson, A probability model of the coincident economic indicators, in Lahiri, K. and G. H. Moore, eds.: Leading Economic Indicators: New Approaches and Forecasting Records, 1991, Cambridge University Press, Cambridge, U.K.

[35] Sullivan, R., A. Timmermann and H. White, Data-snooping, technical trading rule performance, and the bootstrap, *Journal of Finance* **54**, 1999, 1647-1691.

[36] Timmermann, A., Structural breaks, incomplete information, and stock prices, *Journal of Business and Economics Statistics* **19**, 2001, 299-314.

[37] White, H., A reality check for data snooping, *Econometrica* **68**, 2000, 1097-1126.