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The rise and fall of technical trading rule success

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ABSTRACT

The purpose of this paper is to examine the performance of an important set of momentum-based technical trading rules (TTRs) applied to all members of the Dow Jones Industrial Average (DJIA) stock index over the period 1928–2012. Using a set of econometric models that permit time-variation in risk-adjusted returns to TTR portfolios, the results reveal that profits evolve slowly over time, are confined to particular episodes primarily from the mid-1960s to mid-1980s, and rely on the ability of investors to short-sell stocks. These findings are demonstrated to be consistent with theoretical models that predict a relationship between TTR performance and market conditions.

1. Introduction

Technical trading rules (TTRs) are commonly employed in practise as a method of generating buy/sell signals from past data (Gehrig and Menkhoff, 2006). It is, therefore, no surprise that the performance of TTRs has been extensively investigated (see, e.g., Park and Irwin, 2007, for a review). The bulk of the evidence suggests that profits can be obtained when such rules are employed. For instance, in a seminal study of Dow Jones Industrial Average (DJIA) index investing, Brock et al. (1992), henceforth BLL, examine the performance of two important sets of momentum-based TTRs (moving average and trading-range break rules) and show that they perform well over the sample period 1897–1986. Similar evidence is also provided when considering other asset classes; see, e.g., Lukac et al. (1988) for evidence when applied to commodity futures, Lo et al. (2000) for individual stocks, Neely (2002) for foreign exchange, and Faber (2007) for other asset classes.

Despite the documented success of TTRs (and there widespread use within the financial industry), there is a growing literature which casts doubt on their performance particularly over recent periods.[1] Sullivan et al. (1999), henceforth STW, expand the universe of trading rules used by BLL, and control for the effects of data-snooping via use of White's Reality Check bootstrap methodology. Their results suggest that out-of-sample TTR performance does not beat the benchmark model in the period after the end of the BLL sample (1987–1996). This temporal variation in profitability is supported by other studies. For instance, Neely et al. (2009) find that TTRs applied to foreign exchange exhibit variation in performance over time, with profitability largely disappearing after 1990 (see Park and Irwin, 2007, for further evidence). We add to this literature by demonstrating that TTRs applied to DJIA stocks over the period 1928–2012 deliver (risk-adjusted) profits; however, these are highly temporal in nature (with poor performance not confined to recent periods) and depend crucially on the ability of users to short-sell stocks.

The temporal performance of TTRs is consistent with Lo's (2004) adaptive market hypothesis. This conjectures that, inter alia, investment strategies will "*wax and wane, performing well in certain environments and performing poorly in other environments*". It is possible to draw on existing theoretical and empirical evidence to shed light on the environments which are likely to give rise to investment strategy success (and failure). Specifically, within a linearity-generating processes framework, Gabaix (2012) provides compelling theoretical motivation for the time-varying relationship between predictability and the probability of rare large disasters. On the empirical side, Kim et al. (2011) demonstrate that predictability increases during economic and political crises, while Neely et al. (forthcoming) document evidence of variation in TTR performance over the business cycle.[2] The current paper builds on

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[1] It is quite possible that TTRs provide other functions. For instance, Kavajecz and Odders-White (2004) demonstrate that technical analysis provides useful information regarding liquidity provision relating to the depth of the order book.

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this work and demonstrates that profits are only present during periods characterised by certain market conditions.

The current paper contributes to the literature in a number of ways. First, it is one of the first studies to examine a large number of variants of two important sets of TTRs applied to individual stocks over a long sample period (900 rule variants applied to all DJIA stocks over the period 1928–2012). Second, it employs an out-of-sample procedure in which investors update their portfolio of stock positions each month based on the performance (net of transaction costs) of a set of trading rules observed in previous periods. The methods used here are novel in that we go beyond the cumulative wealth approach (equivalently, an expanding window of past performance) and consider past performance that is robust to structural breaks. Third, in contrast to previous studies, we employ sophisticated econometric techniques that allow risk-adjusted TTR performance to change over time and are sufficiently flexible to allow either low or high frequency changes in performance. Fourth, we extend the work of Kim et al. (2011) by demonstrating that this time variation coincides with a variety of measures of market conditions. Fifth, the study documents the importance of short-selling on TTR performance.

The rest of the paper is organised as follows: Sections 2–4 contains a description of the hypotheses, data and methodologies employed, and Section 5 contains the results. The final section concludes.

2. Hypotheses

Four hypotheses are considered. The first two focus on overall TTR performance (with and without investor behaviour restrictions), while the last two examine the dynamics of TTR performance.

2.1. Hypothesis 1: Risk-adjusted TTR portfolio returns exceed risk-adjusted benchmark returns

There is strong theoretical evidence in favour of the notion of predictability in asset returns. The bulk of this evidence highlights the likelihood of observing momentum in stock prices. For instance, Chan et al. (1996) propose a behavioural model in which price continuation occurs due to underreaction to public information.[3] Given this argument, the first hypothesis concerns the overall performance of TTRs. In testing this hypothesis we assume that the TTR portfolio is defined by out-of-sample optimally-updated TTR stock positions, and benchmark returns are given by the returns to a buy-and-hold (BH) strategy or the returns to a risk-free (RF) strategy. Here TTR portfolio returns are calculated net of transaction costs, and are adjusted for risk using the Fama and French (1993) risk factors and the Carhart (1997) momentum risk factor.

2.2. Hypothesis 2: Risk-adjusted TTR portfolio returns change under short sale restrictions

This hypothesis considers the extent to which TTR performance relies on unrestricted investor behaviour. Specifically, we examine the role of short sales on performance. To motivate this hypothesis we note that a number of studies in the extant literature show that short sales make a significant contribution to the profitability of momentum-based trading strategies (see, e.g., BLL, STW, and Lesmond et al., 2004). There is also ample theoretical and empirical evidence in related literatures that shows that short sales play an important role in investment decisions and outcomes. For instance, Diether et al. (2009) document a high degree of short-selling in the US stock market (particularly for large stocks), and that this activity is highly profitable. Similarly, Wang (1998) and Taylor (2012) find that the efficiency of dynamic (managed) portfolios is significantly affected by short-selling restrictions.[4] With these results in mind it follows that TTR performance may be dependent on such restrictions.

2.3. Hypothesis 3: Risk-adjusted TTR portfolio returns are temporal

It is possible to extend Hypothesis 2 by acknowledging the growing evidence of time variation in market efficiency; see, e.g., Lo (2004), Yen and Lee (2008), Lim and Brooks (2011), and Ito and Noda (2012). Consequently, the third hypothesis refines the previous hypotheses by considering whether risk-adjusted TTR portfolio returns change over time. This hypothesis is particularly pertinent to the TTR literature as a number of studies find that TTR profits (predictability) have largely disappeared in the period after the end of the BLL sample period (that is, 1986); see, e.g., STW, Park and Irwin (2007), Neely et al. (2009), and Henkel et al. (2011). Therefore, we examine whether risk-adjusted TTR portfolio returns equal risk-adjusted benchmark returns in the pre-BLL and post-BLL sample periods. Moreover, we relax the implicit assumption underlying previous studies that there is an abrupt performance change around these dates. In particular, we allow the data to decide the speed (and the location(s)) of adjustment and consider whether risk-adjusted TTR portfolio returns change slowly or abruptly over time.

2.4. Hypothesis 4: Risk-adjusted TTR portfolio returns are related to market conditions

To examine the temporal nature of TTR performance in more detail we consider the environments (market conditions) that support TTR success. There are a number of different theoretically and empirically motivated (related) candidates: high probability of rare large disaster periods (Gabaix, 2012), economic contraction periods (see, e.g., Henkel et al., 2011; Han et al., forthcoming; Neely et al., forthcoming), and economic and political crisis periods (Kim et al., 2011). Given this evidence, we consider the following market condition regimes: market volatility, the business cycle (recessionary or expansionary), and the economic/political crisis regimes as defined by Kim et al. (2011). In addition, there is a growing literature that demonstrates that the psychological biases that drive momentum-based predictability are exaggerated during periods of high information uncertainty (see, e.g., Hirshleifer, 2001; Daniel et al., 1998, 2001).[5] Consequently, we consider the following regimes based on proxies for (market-wide) information uncertainty: viz. market (il) liquidity and macroeconomic uncertainty.[6] By considering such a wide variety of determinants we are able to provide a more detailed examination of which market conditions determine TTR performance in comparison to previous studies.[7]

[3] In a similar vein, Friesen et al. (2009) propose a behavioural model in which investors have a biased view of expected information flow in the post-information release period.

[4] See Miller (1977), Diamond and Verrecchia (1987), and Sharpe (1991) for early theoretical investigations, and Rubinstein (2004) for a review of both the extant empirical and theoretical literatures.

[5] See Zhang (2006) for empirical evidence of this relationship within a cross-sectional asset pricing setting.

[6] See Han et al. (forthcoming) for empirical evidence of the positive relationship between TTR performance and volatility within a cross-sectional asset pricing setting.

[7] These variables are closely related to each other. For instance, Engle et al. (2012) document a positive relationship between market illiquidity and market volatility in the U.S. Treasury market, while Diebold and Yilmaz (2008) document a positive relationship between macroeconomic uncertainty and market volatility.

Table 1
DJIA stocks used.

Entry name	Latest name	Start	Finish
Allied Chemical	Honeywell International	01/10/1928	19/02/2008
Aluminum Company of America	Alcoa	01/06/1959	31/12/2012
Anaconda Copper		01/06/1959	09/08/1976
American Can		01/10/1928	16/12/1988
American Express		30/08/1982	31/12/2012
American International Group		08/04/2004	31/12/2012
American Smelting		01/10/1928	01/06/1959
American Sugar		01/10/1928	18/07/1930
American Telephone & Telegraph[a]	AT&T	04/03/1939	31/12/2012
American Tobacco B[a]	American Brands	01/10/1928	30/10/1985
Atlantic Refining		01/10/1928	18/07/1930
Bank of America		19/02/2008	31/12/2012
Bethlehem Steel		01/10/1928	07/03/1997
Borden		18/07/1930	20/11/1935
Caterpillar		06/05/1991	31/12/2012
Coca-Cola[a]		26/05/1932	31/12/2012
Curtiss-Wright		14/09/1929	18/07/1930
Chrysler		01/10/1928	29/06/1979
Cisco Systems		08/06/2009	31/12/2012
Corn Products Refining		15/08/1933	01/06/1959
Drug		26/05/1932	15/08/1933
Eastman Kodak		18/07/1930	08/04/2004
E.I. du Pont de Nemours		20/11/1935	31/12/2012
General Electric		01/10/1928	31/12/2012
General Motors		01/10/1928	08/06/2009
General Railway Signal		01/10/1928	18/07/1930
Goodrich		01/10/1928	18/07/1930
Goodyear		18/07/1930	01/11/1999
Hewlett–Packard		17/03/1997	31/12/2012
Home Depot		01/11/1999	31/12/2012
Hudson Motor		18/07/1930	26/05/1932
Intel		01/11/1999	31/12/2012
International Business Machines[a]		26/05/1932	31/12/2012
International Harvester	Navistar International	01/10/1928	06/05/1991
International Nickel	Inco	01/10/1928	12/03/1987
International Paper		03/07/1956	08/04/2004
International Shoe		26/05/1932	15/08/1933
Johns-Manville		29/01/1930	30/08/1982
Johnson & Johnson		17/03/1997	31/12/2012
J.P. Morgan		06/05/1991	01/01/2001
JP Morgan Chase		01/01/2001	31/12/2012
Kraft Foods		22/09/2008	14/09/2012
Liggett & Myers		18/07/1930	26/05/1932
Loew's		26/05/1932	03/07/1956
Mack Truck		01/10/1928	26/05/1932
McDonald's		30/10/1985	31/12/2012
Merck		29/06/1979	31/12/2012
Microsoft		01/11/1999	31/12/2012
Minnesota Mining & Manufacturing	3M	09/08/1976	31/12/2012
Nash Motors[a]		01/10/1928	04/03/1939
National Cash Register		08/10/1929	26/05/1932
National Distillers		13/08/1934	01/06/1959
National Steel		20/11/1935	01/06/1959
North American		01/10/1928	29/01/1930
Owens-Illinois Glass		01/06/1959	12/03/1987
Paramount Publix		01/10/1928	26/05/1932
Pfizer		08/04/2004	31/12/2012
Philip Morris	Altria Group	30/10/1985	19/02/2008
Postum Inc.	General Foods	01/10/1928	30/10/1985
Procter & Gamble		26/05/1932	31/12/2012
Radio		01/10/1928	26/05/1932
SBC Communications		01/11/1999	31/12/2012
Sears Roebuck		01/10/1928	01/11/1999
Standard Oil (CA)	Chevron	18/07/1930	01/11/1999
Standard Oil (NJ)	Exxon Mobil	01/10/1928	31/12/2012
Swift	Esmark	01/06/1959	29/06/1979
Texas	Texaco	01/10/1928	17/03/1997
Texas Gulf Sulphur		01/10/1928	26/05/1932
The Boeing		12/03/1987	31/12/2012
The Travelers Companies		08/06/2009	31/12/2012
Travellers Group	Citigroup	17/03/1997	08/06/2009
Union Carbide		01/10/1928	01/11/1999
US Steel	USX	01/10/1928	06/05/1991
United Air Transport[a]	United Technologies	18/07/1930	31/12/2012

Table 1 (*continued*)

Entry name	Latest name	Start	Finish
UnitedHealth Group		14/09/2012	31/12/2012
Verizon Communications		08/04/2004	31/12/2012
Victor Talking Machine		01/10/1928	08/01/1929
Wal-Mart Stores		17/03/1997	31/12/2012
Walt Disney		06/05/1991	31/12/2012
Westinghouse Electric		01/10/1928	17/03/1997
Woolworth		01/10/1928	17/03/1997
Wright Aeronautical		01/10/1928	14/09/1929

Notes: This table contains details of the DJIA stocks used in the analysis. The entry name is the name of the stock when entering the index, and the latest name is the name of the stock at the end of the sample period (that is, on exit or on 31/12/2012).

[a] Cases where a stock has left and re-entered the index during the sample periods provided.

3. Data

A number of previous studies use the DJIA index as the trading vehicle upon which the quality of a set of TTRs is assessed (see, e.g., BLL and STW).[8] This choice is primarily driven by its historical importance as a measure of overall stock market performance and its availability over a long period of time (in excess of 100 years of daily data). However, there are two drawbacks associated with this choice. First, previous studies implicitly assume that the same positions are taken in each stock (at each point time) within the DJIA index; consequently, there is a potential loss of information if the stocks within the index exhibit different dynamics. Second, pervious studies may have underestimated the cost of trading as they do not consider the transaction costs associated with individual stocks within the DJIA index. We address these issues by considering the performance of a TTR portfolio consisting of heterogeneous positions in individual stocks (taken from the DJIA index) net of the transaction costs associated with trading each stock.

Starting October 1, 1928 (the first date on which 30 stocks were contained in the DJIA), the daily prices of all stocks within the DJIA index are obtained from the Center for Research in Security Prices (CRSP) US Stock database accessed via the Wharton Research Data Services (WRDS) interface. To minimise microstructure effects, position signals are based on the average of the ask and bid prices, with all prices adjusted for split events and distributions.[9] To account for changes in the components of the DJIA the following methodology is adopted.[10] Starting in October 1, 1928, the full history of the prices of the 30 stocks within the DJIA were collected. On the date of the next component change (January 8, 1929) the full price history of the new set of stocks is collected. The process is repeated up to December 31, 2012, and results in the use of 83 different stocks over the period October 1, 1928, to December 31, 2012. See Table 1 for details of these stocks.

The analysis also makes use of one month Treasury bill rates (the proxy for the risk-free rate), the three Fama–French risk factors (that is, the market premium, the size premium, and the value premium), and the momentum premium. These data were obtained from Kenneth French's data archive: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html. These factors are used in the subsequent analysis to risk adjust the returns to the TTR portfolio. As will be explained below, these portfolios will be constructed over a monthly frequency; consequently, this is the frequency over which the risk factors are collected.

4. Methodology

This section contains details of the TTRs considered, and the ways in which the returns obtained via use of these rules are measured.

4.1. Trading rules

There are a vast number of TTRs employed in practise. To provide focus we follow BLL and consider variants of two popular TTRs: viz. the moving average TTR (MA-TTR) and the trading range break-out TTR (TR-TTR).[11] In general, these momentum-based strategies generate buy/sell signals as follows:

$$S_{i,j,k} = \begin{cases} +1 & \text{if } P_{i,j} > f_{1,k}(P_{i,0},\ldots,P_{i,j-1}) \times g_{1,k}(S_{i,0,k},\ldots,S_{i,j-1,k}), \\ -1 & \text{if } P_{i,j} < f_{2,k}(P_{i,0},\ldots,P_{i,j-1}) \times g_{2,k}(S_{i,0,k},\ldots,S_{i,j-1,k}), \end{cases} \tag{1}$$

where $S_{i,j,k}$ is the signal associated with the ith stock on the jth day generated by the kth variant of the TTR (with a value of zero taken if neither condition holds), $P_{i,j}$ is the price of the ith stock on the jth day, and $f_{1,k}, f_{2,k}, g_{1,k}$, and $g_{2,k}$ are pre-defined functions of past signals or prices.

The MA-TTR is defined as follows. A buy (sell) signal is generated on jth day when the current price crosses the moving average price from below (above). Therefore, in terms of the functions $f_{1,k}$ and $f_{2,k}$ in the above expression we have

$$f_{1,k}(P_{i,0},\ldots,P_{i,j-1}) = f_{2,k}(P_{i,0},\ldots,P_{i,j-1}) = (P_{i,j-n} + \ldots + P_{i,j-1})/n. \tag{2}$$

By contrast, the TR-TTR dictates that a buy (sell) signal is generated on jth day when the current price crosses the recent high (low) from below (above). Formally,

$$f_{1,k}(P_{i,0},\ldots,P_{i,j-1}) = \max(P_{i,j-n},\ldots,P_{i,j-1}), \tag{3a}$$

$$f_{2,k}(P_{i,0},\ldots,P_{i,j-1}) = \min(P_{i,j-n},\ldots,P_{i,j-1}). \tag{3b}$$

One can allow for multiplicative bands and minimum holding periods in both of these TTRs by defining the functions $g_{1,k}$, and $g_{2,k}$ as follows: $g_{1,k}(S_{i,0,k},\ldots,S_{i,j-1,k}) = -\infty$ if $0 < 1_{S_{i,j-c,k}=1} + \cdots + 1_{S_{i,j-1,k}=1} < c$, or $(1+b)$ otherwise; and $g_{2,k}(S_{i,0,k},\ldots,S_{i,j-1,k}) = +\infty$ if $0 < 1_{S_{i,j-c,k}=-1} + \cdots + 1_{S_{i,j-1,k}=-1} < c$, or $(1-b)$ otherwise, where 1_A

[8] The DJIA index is also used in related studies; see, e.g., Kim et al. (2011).

[9] Transaction prices are also collected as these are used in the calculation of transaction costs.

[10] The dates of the component changes are obtained from http://en.wikipedia.org/wiki/Historical_components_of_the_Dow_Jones_Industrial_Average.

[11] The popularity of these linear TTRs is evinced by their widespread use in the extant literature. BLL employ a small number of variants of these TTRs only, while STW consider a larger number of variants. More recently, MA-TTRs have been exclusively used in a number of related studies; see, e.g., Han et al. (forthcoming), for use within an empirical cross-sectional asset pricing context, and Zhu and Zhou (2009) for use within a theoretical portfolio optimisation context.

Table 2
Decomposed performance.

Rule	Strategy	Updating	b-e. c_s	Decomposed return (per annum)			
				Short	Neutral	Long	Total
Panel A: Performance without transaction costs							
BH			n.a.	0.000	0.000	0.033	0.033
				[0.000]	[0.000]	[0.542]	[0.542]
TTR	Fixed (IS)		1.320	0.142	0.000	0.177	0.318
(w short sales)				[0.225]	[0.000]	[0.187]	[0.225]
	Dynamic (OOS)	Rolling	0.881	0.143	0.000	0.177	0.320
				[0.276]	[0.000]	[0.231]	[0.259]
		Expanding	0.648	0.142	0.000	0.175	0.316
				[0.335]	[0.000]	[0.281]	[0.298]
		Av. sub-win.	0.849	0.142	0.000	0.176	0.318
				[0.282]	[0.000]	[0.239]	[0.260]
		Expon. smooth.	0.856	0.139	0.000	0.174	0.313
				[0.287]	[0.000]	[0.238]	[0.270]
TTR	Fixed (IS)		n.a.	0.000	0.000	0.177	0.177
(w/o short sales)				[0.000]	[0.000]	[0.187]	[0.187]
	Dynamic (OOS)	Rolling	n.a.	0.000	0.000	0.177	0.177
				[0.000]	[0.000]	[0.224]	[0.224]
		Expanding	n.a.	0.000	0.000	0.174	0.174
				[0.000]	[0.000]	[0.278]	[0.278]
		Av. sub-win.	n.a.	0.000	0.000	0.177	0.177
				[0.000]	[0.000]	[0.227]	[0.227]
		Expon. smooth.	n.a.	0.000	0.000	0.177	0.177
				[0.000]	[0.000]	[0.225]	[0.225]
Panel B: Performance with transaction costs							
BH			n.a.	0.000	0.000	0.033	0.033
				[0.000]	[0.000]	[0.542]	[0.542]
TTR	Fixed (IS)		0.152	0.022	−0.003	0.055	0.074
(w short sales)				[0.338]	[0.003]	[0.288]	[0.327]
	Dynamic (OOS)	Rolling	0.139	0.017	−0.002	0.046	0.061
				[0.350]	[0.003]	[0.285]	[0.355]
		Expanding	0.151	0.022	−0.003	0.055	0.074
				[0.338]	[0.003]	[0.288]	[0.327]
		Av. sub-win.	0.127	0.011	−0.002	0.046	0.055
				[0.340]	[0.004]	[0.285]	[0.345]
		Expon. smooth.	0.124	0.011	−0.002	0.045	0.054
				[0.345]	[0.005]	[0.294]	[0.358]
TTR	Fixed (IS)		n.a.	0.000	−0.008	0.027	0.019
(w/o short sales)				[0.000]	[0.007]	[0.352]	[0.356]
	Dynamic (OOS)	Rolling	n.a.	0.000	−0.017	0.020	0.003
				[0.000]	[0.023]	[0.313]	[0.314]
		Expanding	n.a.	0.000	−0.007	0.017	0.011
				[0.000]	[0.007]	[0.294]	[0.297]
		Av. sub-win.	n.a.	0.000	−0.017	0.030	0.013
				[0.000]	[0.023]	[0.299]	[0.301]
		Expon. smooth.	n.a.	0.000	−0.017	0.026	0.009
				[0.000]	[0.022]	[0.297]	[0.299]

Notes: This table contains the decomposed mean of returns, standard deviation of returns (in parentheses), and break-even short sale costs (b-e. c_s) associated with various rules, updating strategies, benchmarks, and transaction cost assumptions. These measures are provided for the BH strategy and the optimal TTR strategy (based on a variety of different MA-TTR and TR-TTR strategies). Annual returns associated with short, neutral, and long positions are provided (as is the sum of these returns over these positions).

indicates whether condition A holds, and b and c pre-selected constants.

To avoid selection of parameters values in the above rules that may encourage or discourage a particular outcome, we adopt values that closely span the space used in BLL and STW. Specifically, the following values are assumed in the MA-TTR and TR-TTR:

$$n \in \{5, 10, 15, 20, 25, 50, 100, 150, 200, 250\},$$

$$b \in \{0, 0.001, 0.005, 0.01, 0.015, 0.02, 0.03, 0.04, 0.05\},$$

$$c \in \{0, 5, 10, 25, 50\}.$$

As all combinations of these parameters are used, we consider 450 MA-TTR and 450 TR-TTR variants.

4.2. Portfolio construction

The above rules are applied to daily excess returns to each DJIA stock.[12] The returns to each rule are then averaged over all days (within each month) and over all stocks to give a monthly frequency (average) portfolio return. Formally, portfolio returns (in excess of the risk-free rate) in the tth month generated by the kth rule net of proportional transaction costs are given by

$$Y_{t,k} = \frac{1}{C}\frac{1}{D}\sum_{i=1}^{C}\sum_{j'=1}^{D}\left(\frac{1 + R_{i,D(t-1)+j'}S_{i,D(t-1)+j',k}}{1 + |\Delta S_{i,D(t-1)+j',k}|tc_{i,D(t-1)+j'}/2}\right) - 1, \qquad (4)$$

[12] The rules were also applied to the index values, with homogenous positions in all DJIA stocks taken on the basis on a single signal. However, the subsequent profits were uniformly lower than those produced when rules are applied to (and heterogenous positions taken in) individual stocks.

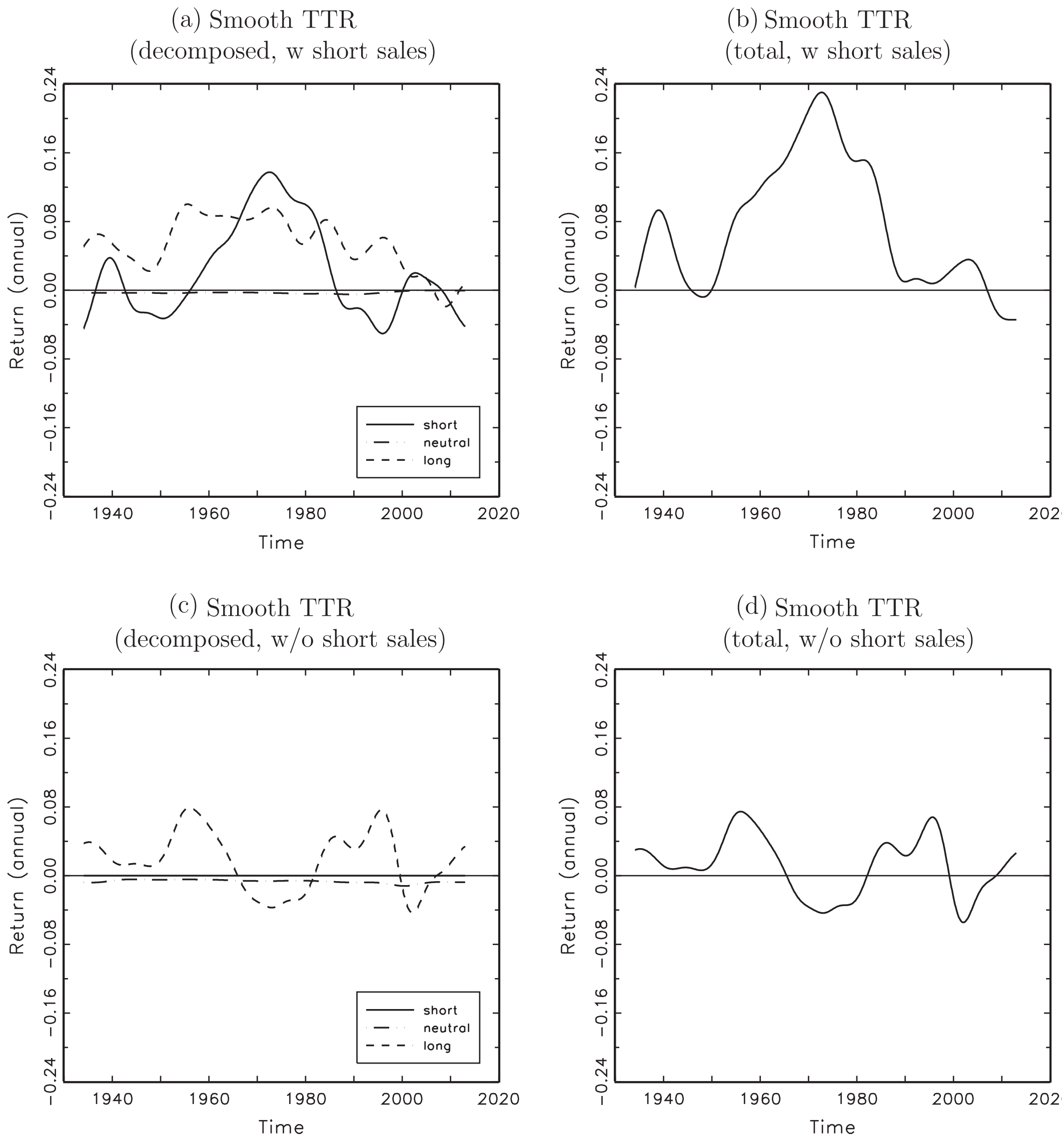

Fig. 1. Technical rule excess returns. This figure contains smoothed time series plots of the decomposed excess returns associated with the TTR strategy (based on the expanding window updating method), the RF benchmark, and two short sale assumptions. The smoothing is achieved via use of a kernel-based estimator, with a Gaussian kernel and bandwidth of $0.5T^{-0.4}$ assumed.

where $R_{i,D(t-1)+j'}$ is the excess return to the ith stock on the $D(t-1)+j'$th day, $tc_{i,D(t-1)+j'}$ is the proportional transaction cost associated with the ith stock on the $D(t-1)+j'$th day, C is the total number of stocks considered (that is, 30), and D is the total number of trading days in a month.[13]

Proportional transaction costs are based on Roll's (1984) effective spread estimator. This measure uses the observed autocovariance of price changes associated with each stock calculated using all transaction prices for the ith stock up to the jth day; specifically,

$$tc_{i,j} = 2\left(-\frac{1}{j}\sum_{j^*=1}^{j}\Delta\widetilde{P}_{i,j^*} \times \Delta\widetilde{P}_{i,j^*-1}\right)^{1/2} \times \left(\frac{1}{j}\sum_{j^*=1}^{j}P_{i,j^*}\right)^{-1}, \qquad (5)$$

where $\Delta\widetilde{P}_{i,j^*}$ denotes demeaned price differences.[14] While there are a large number of alternative spread estimators available, the Roll effective spread estimates have been shown to be moderately to highly correlated with estimates based on direct observation of the trade-weighted effective spreads in the NYSE TAQ database (see Table IV and V in Corwin and Schultz, 2012).[15]

4.3. Portfolio selection

The next stage of the analysis concerns the choice of trading rule at each point in time (that is, each month) based on the current information set (that is, the out-of-sample updating method); this amounts to the selection of k in (4) at each point within the sample. In particular, each investor must decide which of the TTR variants to use during the next period (month). We consider a number of different out-of-sample updating methods, all of which are time consistent in that they are based on past performance; specifically,

[13] The use of excess returns means that long stock positions are funded by borrowing at the risk-free rate, while short stock positions are characterised by funds invested at the risk-free rate.

[14] In instances where the covariance of demeaned price differences is positive we follow common practise and set the proportional transaction cost to zero.

[15] This correlation is relatively higher for stocks in the largest size quintile.

Table 3
Dominance tests.

Rule	Sample/regime	Sample size	TTR ≻ RF		TTR ≻ BH	
			FO	SO	FO	SO
Panel A: Sample period analysis						
TTR (w short sales)	1934–1939	72	0.000	0.001	0.149	0.455
	1940–1949	120	0.000	0.000	0.001	0.018
	1950–1959	120	0.000	0.027	0.000	0.054
	1960–1969	120	0.000	0.422	0.432	1.000
	1970–1979	120	0.000	0.509	0.533	1.000
	1980–1989	120	0.000	0.005	0.063	0.999
	1990–1999	120	0.000	0.000	0.001	0.006
	2000–2012	156	0.000	0.000	0.005	0.332
	1934–1986 (pre-BLL sample)	636	0.000	0.000	0.000	1.000
	1987–2012 (post-BLL sample)	312	0.000	0.000	0.000	0.007
	1934–2012 (full sample)	948	0.000	0.000	0.000	1.000
TTR (w/o short sales)	1934–1939		0.000	0.022	0.000	0.013
	1940–1949		0.000	0.000	0.000	0.002
	1950–1959		0.000	0.011	0.000	0.000
	1960–1969		0.000	0.000	0.000	0.807
	1970–1979		0.000	0.026	0.009	0.293
	1980–1989		0.000	0.000	0.002	0.085
	1990–1999		0.000	0.001	0.000	0.000
	2000–2012		0.000	0.000	0.000	0.006
	1934–2012 (pre-BLL sample)		0.000	0.000	0.000	0.001
	1934–1986 (post-BLL sample)		0.000	0.000	0.000	0.000
	1987–2012 (full sample)		0.000	0.000	0.000	0.000
Panel B: Market volatility regimes						
TTR (w short sales)	Low	474	0.000	0.002	0.000	1.000
	High	474	0.000	0.000	0.000	0.033
TTR (w/o short sales)	Low		0.000	0.000	0.000	0.005
	High		0.000	0.000	0.000	0.000
Panel C: Business cycle regimes						
TTR (w short sales)	Expansion	805	0.000	0.000	0.000	1.000
	Contraction	143	0.000	0.001	0.149	1.000
TTR (w/o short sales)	Expansion		0.000	0.000	0.000	0.000
	Contraction		0.000	0.000	0.000	0.579
Panel D: Economic/political crisis regimes						
TTR (w short sales)	Non-crisis	660	0.000	0.000	0.000	0.167
	Crisis	288	0.000	0.008	0.095	1.000
TTR (w/o short sales)	Non-crisis		0.000	0.000	0.000	0.000
	Crisis		0.000	0.000	0.000	0.030
Panel E: Market illiquidity regimes						
TTR (w short sales)	Low	429	0.000	0.000	0.000	0.028
	High	519	0.000	0.000	0.003	1.000
TTR (w/o short sales)	Low		0.000	0.000	0.000	0.000
	High		0.000	0.000	0.000	0.014
Panel F: Macroeconomic uncertainty regimes						
TTR (w short sales)	Low	474	0.000	0.000	0.000	0.009
	High	474	0.000	0.000	0.011	1.000
TTR (w/o short sales)	Low		0.000	0.000	0.000	0.000
	High		0.000	0.000	0.000	0.014

Notes: This table contains the first-order (FO) and second-order (SO) stochastic dominance test p-values associated with various rules, samples/regimes, and benchmarks. Two null hypotheses are examined using the stochastic dominance tests: that the TTR strategy (based on the expanding window updating method) dominates the RF or BH strategies. The p-values are calculated using a 1000-repetition version of the recentred bootstrap procedure proposed by Linton et al. (2005).

Expanding window updating :

$$k_t^* = \underset{k}{\operatorname{argmin}} - \sum_{h=1}^{t-1} \frac{1}{t-1} Y_{t-h,k}, \tag{6a}$$

Rolling window updating :

$$k_t^* = \underset{k}{\operatorname{argmin}} - \sum_{h=1}^{m} \frac{1}{m} Y_{t-h,k}, \tag{6b}$$

Average sub-window updating :

$$k_t^* = \underset{k}{\operatorname{argmin}} - \frac{1}{t-m} \sum_{i=m}^{t-1} \sum_{h=1}^{i} \frac{1}{i} Y_{t-h,k}, \tag{6c}$$

Exponential smoothing window updating :

$$k_t^* = \underset{k}{\operatorname{argmin}} - \frac{1-\delta}{1-\delta^{t-1}} \sum_{h=1}^{t-1} \delta^{h-1} Y_{t-h,k}, \tag{6d}$$

Table 4
Estimated factor model details.

Rule	Model	Estimated parameter							Fit	
		$\hat{c}_0$	$\hat{c}_1$	$\hat{\phi}$	$\hat{\beta}_1$	$\hat{\beta}_2$	$\hat{\beta}_3$	$\hat{\beta}_4$	AIC	SBC
Panel A: RF benchmark										
TTR	LR (no dummy)	0.083**			−0.073**	−0.055*	−0.012	−0.019	0.592	0.623
(w ss)	LR (volatility)	0.097**	−0.027		−0.074**	−0.052*	−0.011	−0.021	0.609	0.645
	LR (recession)	0.077**	0.038		−0.072**	−0.055*	−0.008	−0.017	0.609	0.645
	LR (crisis)	0.068**	0.049*		−0.070**	−0.055*	−0.010	−0.018	0.606	0.642
	LR (illiquidity)	0.027	0.104**		−0.075**	−0.049*	−0.012	−0.028*	0.585	0.621
	LR (uncertainty)	0.054**	0.058*		−0.069**	−0.058*	−0.016	−0.019	0.603	0.639
	STR (linear)	0.008	0.111**		−0.074**	−0.056*	−0.014	−0.022*	0.589	0.635
	STR (quadratic)	0.022	0.154**		−0.069**	−0.060*	−0.016	−0.026*	0.566	0.618
	STR (cubic)	0.017	0.204**		−0.066**	−0.063**	−0.017	−0.025*	0.567	0.624
	SS (MRC)	0.067**		0.994**	−0.068**	−0.062*	−0.018	−0.024*	0.564†	0.605†
	SS (RWC)	0		1	−0.068**	−0.062*	−0.019	−0.025*	0.581	0.612
TTR	LR (no dummy)	−0.024**			0.436**	−0.116**	0.006	0.045**	−0.468†	−0.437†
(w/o ss)	LR (volatility)	−0.030**	0.011		0.438**	−0.114**	0.012	0.047**	−0.452	−0.416
	LR (recession)	−0.025**	0.005		0.437**	−0.113**	0.012	0.046**	−0.451	−0.415
	LR (crisis)	−0.020**	−0.013		0.437**	−0.113**	0.012	0.046**	−0.452	−0.416
	LR (illiquidity)	−0.014	−0.019		0.438**	−0.114**	0.012	0.048**	−0.453	−0.418
	LR (uncertainty)	−0.023*	−0.003		0.437**	−0.113**	0.012	0.046**	−0.451	−0.415
	STR (linear)	−0.006	−0.020		0.437**	−0.113**	0.013	0.047**	−0.448	−0.402
	STR (quadratic)	−0.006	−0.023		0.439**	−0.114**	0.015	0.048**	−0.447	−0.395
	STR (cubic)	−0.005	−0.022		0.437**	−0.113**	0.013	0.047**	−0.443	−0.387
	SS (MRC)	−0.024**		0.935**	0.436**	−0.115**	0.007	0.046**	−0.464	−0.423
	SS (RWC)	0		1	0.436**	−0.116**	0.006	0.045**	−0.443	−0.412
Panel B: BH benchmark										
TTR	LR (no dummy)	0.115**			−0.988**	0.109**	−0.111**	0.068**	1.069	1.099
(w ss)	LR (volatility)	0.138**	−0.044		−0.990**	0.110**	−0.117**	0.064**	1.084	1.120
	LR (recession)	0.106**	0.056*		−0.987**	0.105**	−0.112**	0.071**	1.084	1.120
	LR (crisis)	0.095**	0.066*		−0.986**	0.104**	−0.116**	0.069**	1.081	1.117
	LR (illiquidity)	0.041*	0.137**		−0.992**	0.112**	−0.117**	0.055**	1.059	1.095
	LR (uncertainty)	0.084**	0.063*		−0.984**	0.102**	−0.116**	0.067**	1.081	1.117
	STR (linear)	0.025	0.134**		−0.992**	0.101**	−0.122**	0.061**	1.066	1.112
	STR (quadratic)	0.022	0.152**		−0.990**	0.104**	−0.125**	0.064**	1.061	1.112
	STR (cubic)	0.020	0.153**		−0.990**	0.105**	−0.125**	0.063**	1.063	1.120
	SS (MRC)	0.099**		0.995**	−0.983**	0.102**	−0.117**	0.063**	1.054†	1.095†
	SS (RWC)	0		1	−0.983**	0.102**	−0.118**	0.062**	1.071	1.101
TTR	LR (no dummy)	0.008			−0.479**	0.048**	−0.092**	0.133**	−0.433†	−0.402†
(w/o ss)	LR (volatility)	0.011	−0.007		−0.479**	0.047**	−0.094**	0.132**	−0.413	−0.378
	LR (recession)	0.004	0.024		−0.478**	0.046**	−0.092**	0.134**	−0.415	−0.379
	LR (crisis)	0.006	0.004		−0.479**	0.047**	−0.094**	0.132**	−0.413	−0.377
	LR (illiquidity)	0.001	0.014		−0.479**	0.047**	−0.094**	0.131**	−0.414	−0.379
	LR (uncertainty)	0.007	0.002		−0.479**	0.047**	−0.094**	0.132**	−0.413	−0.377
	STR (linear)	−0.066*	0.076*		−0.481**	0.048*	−0.100**	0.132**	−0.413	−0.367
	STR (quadratic)	−0.000	0.025		−0.482**	0.048**	−0.100**	0.132**	−0.411	−0.359
	STR (cubic)	0.000	0.025		−0.480**	0.050**	−0.098**	0.136**	−0.408	−0.352
	SS (MRC)	0.008		0.929**	−0.479**	0.048**	−0.091**	0.133**	−0.430	−0.389
	SS (RWC)	0		1	−0.479**	0.048**	−0.092**	0.133**	−0.408	−0.377

Notes: This table contains the estimated parameters and fits associated with various versions of the LR, STR, and SS factor models (each of which includes the three Fama–French factors plus the momentum factor) applied to TTR excess returns (based on the expanding window updating method), with various benchmarks assumed. The parameters c_0 and c_1 provide measures of the risk-adjusted excess returns to the TTR portfolio during each regime (LR and STR models only); ϕ measures the persistence in risk-adjusted excess returns to the TTR portfolio (SS models only); and $\beta_1, \beta_2, \beta_3$, and β_4, measure the sensitivity to each risk factor. Fit is given by the Akaike information criterion (AIC) and Schwarz Bayesian criterion (SBC). The model with the best fit is indicated by the † symbol. Rejections of the null hypothesis that each parameter equals zero at the 5% and 1% level are indicated by superscripts $*$ and $**$, respectively.

where k_t^* represents the optimal TTR variant (taken from all MA-TTR and TR-TTR variants), $m = 60$ and $\delta = 0.95$.[16] Given this choice of m, the out-of-sample period $t \in \{m+1, \ldots, T\}$ is assumed to start in January 1934 and end in December 2012 for all updating methods.

The expanding window updating procedure is equivalent to using cumulative wealth as the metric for the choice of rule to use in the next period (see, e.g., sections IV and V in STW for use of cumulative wealth). The use of the other updating methods is motivated by the documented benefits of their use within a wider forecasting context. For instance, Pesaran and Pick (2011) and Pesaran et al. (2011) document the advantages of using average sub-window and exponential smoothing window updating in the presence of structural breaks within an economic forecasting context.

4.4. Measuring performance

Having obtained a series of portfolio returns associated with each of the above updating methods, we proceed with an analysis of these returns. Two different testing methodologies are used to assess the quality of these returns, each of which is described below.

4.4.1. Stochastic dominance tests

To test the risk-adjusted performance of the TTR portfolio, we consider whether it stochastically dominates a particular

[16] The choice of $m = 60$ reflects the common use of five-year rolling windows in the finance literature.

benchmark. To this end, the test statistic associated with the null hypothesis that the TTR strategy s-order stochastically dominates a benchmark strategy is given by the generalised Kolmogorov–Smirnov statistic originally proposed by McFadden (1989):

$$D_s = \sqrt{T}\min_{i\neq j}\sup_{y\in\mathbb{R}}\{\mathcal{I}_s(F(y)) - \mathcal{I}_s(F_0(y))\}, \tag{7a}$$

where

$$\mathcal{I}_s(F(y)) = \begin{cases} F(y) = \Pr(Y_t \leqslant y), & \text{if } s = 1, \\ \int_{-\infty}^{y}\mathcal{I}_{s-1}(F(y'))dy', & \text{otherwise}, \end{cases} \tag{7b}$$

and Y_t is the out-of-sample excess return to the optimal TTR portfolio. To allow for mutually dependent data, a recentred bootstrap procedure is used to calculate the p-value associated with the empirical counterpart to $D_s^{(i)}$; see Linton et al. (2005) for further details of this procedure within a general context.

4.4.2. Factor-based tests

4.4.2.1. The general form. As an alternative to the above test, we also consider tests based on augmentations of the factor model originally proposed by Fama and French (1993). Specifically, we assume that TTR portfolio returns evolve according to the following time-varying parameter model with Gaussian state-space (SS) form:

$$Y_t = \alpha_t + \boldsymbol{\beta}'\mathbf{Z}_t + \epsilon_t, \quad \epsilon_t \sim \mathrm{NID}(0, \sigma_\epsilon^2), \tag{8a}$$

$$\alpha_{t+1} = c_t + \phi\alpha_t + \eta_t, \quad \eta_t \sim \mathrm{NID}\left(0, \sigma_\eta^2\right), \tag{8b}$$

where α_{t+1} is the pricing error (Jensen's alpha measure), $\boldsymbol{\beta}$ is a (4×1) vector of factor loadings, $\mathbf{Z}_t$ is a (4×1) vector of factor returns given by the three Fama–French risk factors (that is, the market premium, the size premium, and the value premium), and the momentum premium, and $\alpha_1 \sim \mathrm{N}(a, P)$.

The state variable α_{t+1} is the 'predicted' risk-adjusted excess return to the TTR portfolio. Consequently, the performance of this portfolio can be assessed via consideration of the size and significance of the state variable. Given the importance of this variable we consider three different (restricted) versions of the above SS form – each of which differentiates itself in terms of the evolution of the state variable.

4.4.2.2. Linear regression models. The conventional approach to measuring risk-adjusted returns assumes that the state variable has no random component and is given by a constant term. We augment this basic approach by allowing time variation in the state variable via a dummy variable. Specifically,

$$\alpha_{t+1} = c_0 + c_1 D_t, \tag{9}$$

where D_t is a dummy variable that equals unity during a particular market condition regime (e.g., during recessions) and zero otherwise. It follows that c_0 and $c_0 + c_1$ are the respective pricing errors during each regime. The absence of the random component in the state variable equation means that this representation coincides with the linear regression (LR) model. An advantage of using this model is that it is simple to estimate and permits testing for variation in pricing error across regimes using conventional testing methods. Models based on this framework are henceforth referred to as the LR (no dummy) and LR (with dummy) models.

4.4.2.3. Smooth transition regression models. The above model assumes that TTR performance varies only over pre-specified regimes (or over the entire sample period if no dummy variable is included). To relax this assumption we consider a smooth transition regression (STR) model in which the state variable is allowed to vary over time in a continuous way. Specifically, we consider the following specification:

$$\alpha_{t+1} = c_0 + c_1 F_t, \tag{10a}$$

where F_t is a transition function that permits structural change in the parameter values. We follow Lin and Teräsvirta (1994) and achieve this by allowing the transition function to be non-linearly dependent on time t. Specifically, we consider the following flexible specification:

$$F_t = ((1 + \exp(-\gamma(t^i + \theta_1 t^{i-1} + \cdots + \theta_{i-1}t + \theta_i)))^{-1}, \quad \forall i \in \{1,2,3\}. \tag{10b}$$

The order of the above model (that is, i) determines the complexity of the transition between regimes, while γ determines the speed of transition between these regimes.[17] We consider linear ($i = 1$), quadratic ($i = 2$), and cubic ($i = 3$) versions of this model, henceforth referred to as the STR (linear), STR (quadratic), and STR (cubic) models.

4.4.2.4. State space models. It could be argued that the STR models predetermine (and oversimplify) the profile of risk-adjusted TTR portfolio returns over time. To address this potential shortcoming we consider an alternative factor-based model in which the coefficients are allowed to vary over time in a less prescribed fashion. In particular, the state variable is assumed to follow a mean reverting process:

$$(\alpha_{t+1} - c_0) = \phi(\alpha_t - c_0) + \eta_t, \tag{11}$$

where ϕ measures the degree of persistence in the state variable. As an alternative the restriction that $\phi = 1$ can be imposed to yield the following simplified representation:

$$\alpha_{t+1} = \alpha_t + \eta_t. \tag{12}$$

The models that assume the above processes are henceforth respectively referred to as the state space mean reverting coefficient (SS (MRC)), and state space random walk coefficient (SS (RWC)) models. See Mergner (2009) for further details of these models.

4.5. Measures of market conditions

The LR models described above make use of a variety of dummy variables that each represent a different market condition regime. The following market condition regimes are considered:

4.5.1. Market volatility regimes

The high (low) market volatility regime is defined as periods in which market volatility is above (below) its median value, with the dummy variable taking a value of unity (zero) in the high (low) volatility regime. Market volatility is defined as the conditional variance associated an AR(1)-GARCH(1,1) model applied to monthly frequency S&P 500 log returns over the period January 1926 to December 2012.

4.5.2. Business cycle regimes

These regimes are based on the NBER Business Cycle Dating Committee classification of contraction and expansion periods, such that the dummy variable equals unity during periods in which economic activity contracts (recession periods) and zero otherwise; see http://www.nber.org/cycles.html for the business cycle dates.

4.5.3. Economic/political crisis regimes

[17] See Lin and Teräsvirta (1994) for graphical examples of the shapes made by these functions.

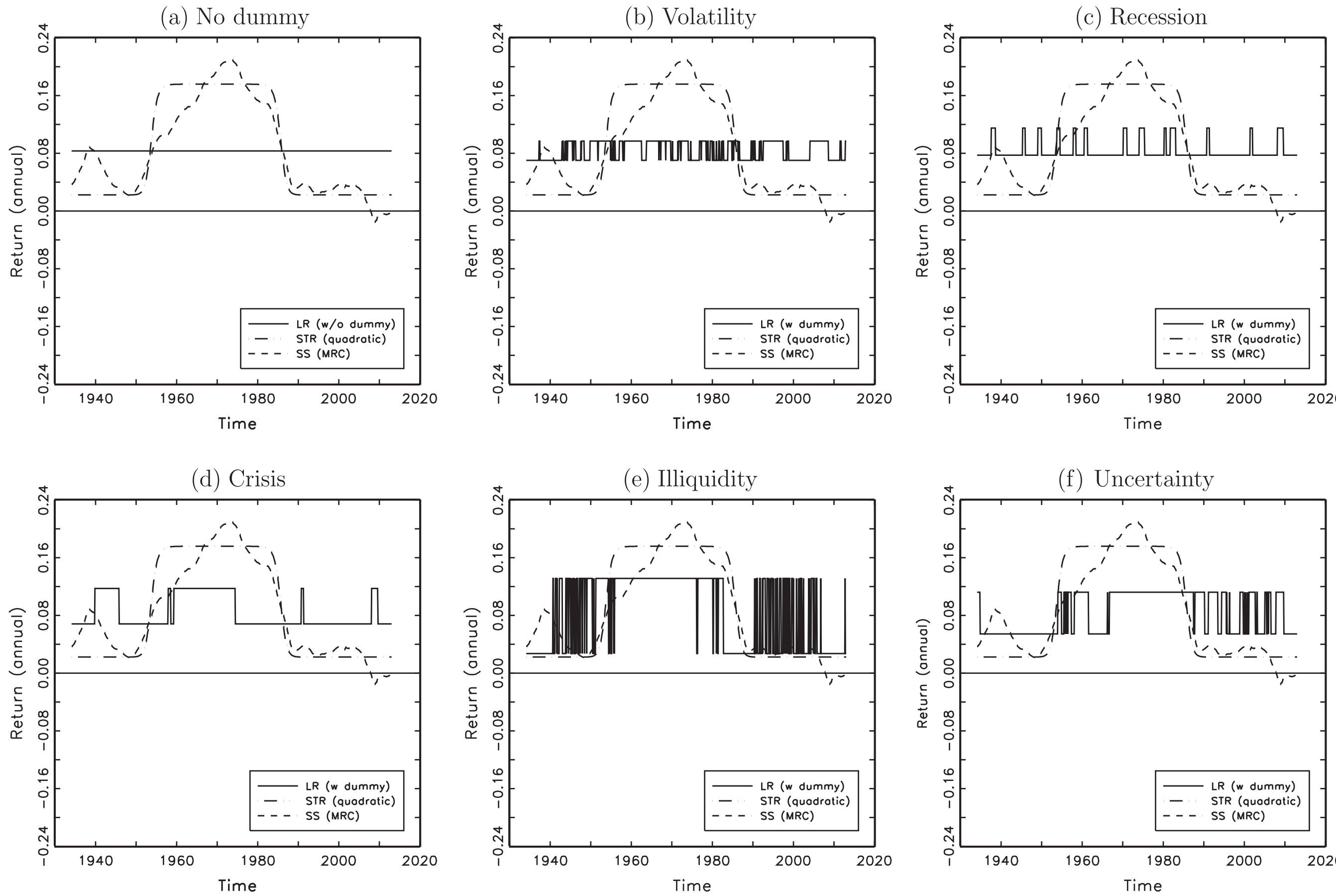

Fig. 2. Comparing risk-adjusted excess returns (RF benchmark). This figure contains the predicted risk-adjusted excess returns associated with the TTR portfolio (based on the expanding window updating method), and the RF benchmark. The predicted values are based on the LR (with and without a dummy variable), STR (quadratic) and SS (MRC) models.

The dummy variable associated with these regimes equals unity during periods of economic/political crisis as defined by the subjective evaluation of Kim et al. (2011) and zero otherwise. More specifically, we use their 'fundamental crisis' dates as published in Table 1 of their paper to define the crisis periods.

4.5.4. Market illiquidity regimes

The high (low) market illiquidity regime is defined as periods in which the log of market illiquidity is above (below) its expected value, with the dummy variable taking a value of unity (zero) in the high (low) market illiquidity regime.[18] Market illiquidity is measured using the turnover version of the price impact estimator initially proposed by Amihud (2002). This is applied to all DJIA stocks over a daily frequency. The resulting values are averaged over all stocks and all days in each month to give a market-wide monthly frequency illiquidity estimate.

4.5.5. Macroeconomic uncertainty regimes

The high (low) macroeconomic uncertainty regime is defined as periods in which macroeconomic uncertainty is above (below) its median value, with the dummy variable taking a value of unity (zero) in the high (low) macroeconomic uncertainty regime. Given the recently documented positive relationship between macroeconomic uncertainty and the volatility of returns to government debt (Arnold and Vrugt, 2010), macroeconomic uncertainty is defined as the conditional variance associated with an AR(1)-GARCH(1,1) model applied to monthly frequency Treasury bill rates over the period January 1926 to December 2012.

5. Results

This section contains the results associated with the above models.

5.1. Initial findings

The results in Table 2 contain information pertaining to the performance of various trading strategies. In particular, the mean and standard deviation (in parentheses) of returns associated with the BH portfolio, the best (in-sample) TTR portfolio over the whole sample, and the optimal TTR portfolios based on different out-of-sample updating methods. This information is given for each type of position held (short, neutral, long, and total), with and without transaction costs, and with and without the short sale restriction imposed. In addition, we also provide an estimate of the break-even short sale cost (b-e. c_s) under these assumptions.[19]

The results demonstrate that TTRs offer investors higher mean returns with lower risk (standard deviation) than the BH strategy.

[18] Market illiquidity contains a strong trend component. Consequently, the expected value of market illiquidity is given by the fitted value from a regression of the log of market illiquidity on a constant and a linear trend. The use of log market illiquidity ensures that the trend is linear. Further details of the estimated regression are available on request.

[19] The break-even short sale cost is given by the mean return to the TTR portfolio divided by the proportional number of short positions held.

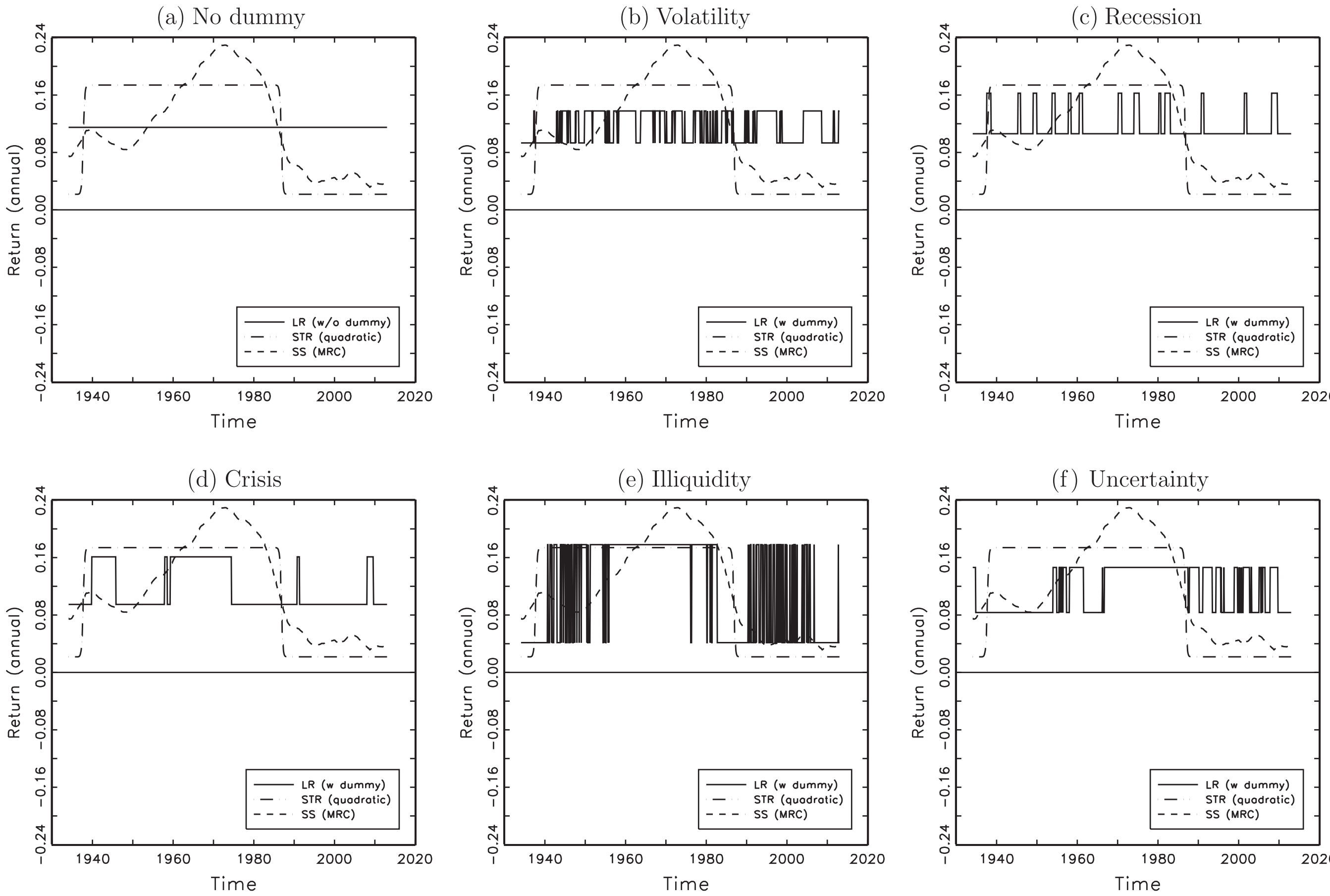

Fig. 3. Comparing risk-adjusted excess returns (BH benchmark). This figure contains the predicted risk-adjusted excess returns associated with the TTR portfolio (based on the expanding window updating method), and the BH benchmark. The predicted values are based on the LR (with and without a dummy variable), STR (quadratic) and SS (MRC) models.

For instance, in the absence of transaction costs, the mean excess return to the TTR portfolio (with expanding window updating) is 31.6% per annum, with a standard deviation of 29.8% per annum (cf. respective figures of 3.3% and 54.2% for the BH strategy). When transactions costs are taken into account mean excess returns fall dramatically; however, the TTR strategy still dominates with a mean excess return of 7.4% per annum, and a standard deviation of 32.7% per annum.[20] Moreover, a healthy break-even short sale cost of 15.1% per annum is observed. These results are fairly robust to the updating methods used, though expanding window updating (as used in BLL and STW) does appear to deliver the highest level of performance.

Decomposing returns according to the type of position held reveals interesting findings. The excess returns to long positions are greater than the excess returns to short positions (see BLL and STW for similar findings), while the excess returns to the neutral positions are necessarily negative when transaction costs are incorporated. However, when short sales are not permitted the mean excess returns to the TTR portfolio fall dramatically and are less than those associated with the BH strategy.[21] Thus it would appear that while short portfolio returns are not a large as long position returns, they still make a valuable contribution to TTR portfolio returns in the presence of transaction costs.

To gain further insight into the relative performance of TTRs in the presence of transaction costs, time series plots of smoothed excess returns to the TTR positions are given in Fig. 1.[22] These plots are provided for each type of position held, with and without the short sale restriction imposed, with transaction costs incorporated, and are based on expanding window updating.[23]

The plots reveal a number of interesting features of the data. First, TTR performance appears temporal in that there appears to be evidence of prolonged positive excess returns to the TTR portfolio around the early 1970s, with all other periods characterised by returns that appear close to zero. Second, this time variation in excess returns to the TTR portfolio is largely driven by the variation in excess returns to short positions, with a distinctive peak around the early 1970s. By contrast, excess returns to long positions appear more evenly distributed over time. Third, short-selling restrictions have an adverse impact on excess returns, with little evidence of large positive TTR excess returns during any period.

5.2. Stochastic dominance tests

To examine the initial findings in more detail, we conduct the stochastic dominance tests described in Section 4.4. The results in Table 3 contain the stochastic dominance p-values, associated with the optimal TTR portfolio, the RF and BH benchmarks, with

[20] See Lesmond et al. (2004) for similar evidence of the dramatic adverse impact of transaction costs on momentum strategy performance.

[21] The short sale restriction is achieved by replacing cases where $S_{i,j,k}$ equals minus unity in (1) with $S_{i,j,k}$ equals zero.

[22] Smoothing is achieved via use of a kernel-based estimator, with a Gaussian kernel and bandwidth of $0.5T^{-0.4}$ assumed.

[23] These assumptions are maintained in the subsequent analysis.

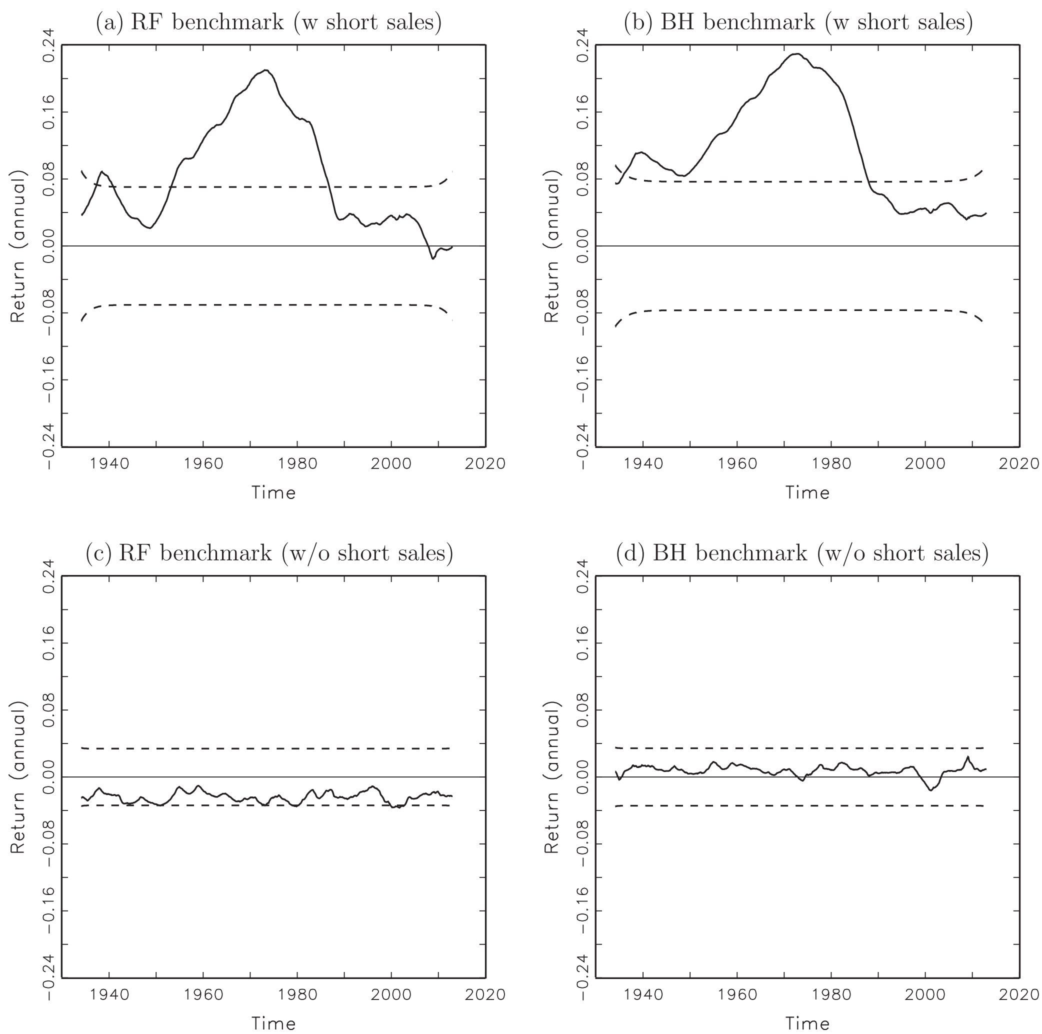

Fig. 4. Risk-adjusted excess returns (SS (MRC) model). This figure contains the predicted risk-adjusted excess returns (and 95% confidence interval centred on zero) associated with the TTR portfolio (based on the expanding window updating method), two benchmarks, and two short sale assumptions. The predicted values are based on the SS (MRC) model.

and without the short sale restriction imposed. In addition to conducting the stochastic dominance tests over the full sample, they are performed for each decade in the sample, in the pre-BLL and post-BLL sample periods, and in each of the market condition regimes described in Section 4.5.

The results associated with the full sample period (1934–2012) confirm the results in Table 2 that TTRs offer investors higher mean returns with lower risk than the BH strategy. This is translated into second-order stochastic dominance. In particular, the null hypothesis that the TTR strategy second-order stochastically dominates the BH strategy cannot be rejected. When the sample is sub-divided into separate sample periods, there are clear differences in the results. In particular, if we truncate the sample period with an endpoint that coincides with the end of the BLL sample period (that is, 1934–1986) then the TTR strategy is superior to the BH strategy in terms of second-order stochastic dominance. By contrast, in the period after 1986 (that is, over the period 1987–2012), the performance of the TTR strategy takes a dramatic downturn. Importantly, there is no evidence of stochastic dominance over this sample period. This evidence is consistent with the notion that TTR performance has deteriorated over recent periods (see, e.g., STW).

It is possible to extend the subperiod analysis by performing the stochastic dominance tests for each decade of the sample, and during each market condition regime. The results show that the TTR strategy tends to dominate the RF and BH strategies in the 1960–1969 and 1970–1979 decades only. Furthermore, there is variation in the results over the market condition regimes. Perhaps most notable there is a switch from not being able to reject the null of (second-order) dominance of the TTR strategy over the BH strategy to rejection of this null (at the 5% level) when one compares the low market volatility to high market volatility, high market illiquidity to low market illiquidity, and high macroeconomic uncertainty to low macroeconomic uncertainty regimes.[24]

The results in Table 3 also suggest that short sales make a significant contribution to the success of the TTR strategy. This is evinced by the fact that if we repeat the above analysis under the restriction that short sales are not allowed then a different conclusion is drawn. Specifically, the null hypothesis that the TTR strategy second-order stochastically dominates competing strategies is rejected over most sample periods and market condition regimes. Thus the evidence supports the results in Table 2 that suggest that the ability to short-sell stocks is crucial to investors when securing superior returns.

[24] The results associated with the market volatility regime contradict the cross-sectional evidence in Han et al. (forthcoming), which shows that TTR strategies yield higher returns for high volatility stocks in comparison to low volatility stocks.

Table 5
The determinants of TTR performance.

Dependent variable	Independent variable	Div. assumption	FM-OLS parameter			Coint. test	
			$\widehat{\gamma}_0$	$\widehat{\gamma}_0$	$\overline{R}^2$	EG	PO
Panel A: RF benchmark							
STR (quadratic)	LR (volatility)	Excluded	−0.045	1.549**	0.037	1.294	1.360
risk-adj. return	LR (recession)		0.025	0.706	0.007	0.714	0.862
	LR (crisis)		−0.020	1.256**	0.129	1.351	1.461
	LR (illiquidity)		−0.004	1.050**	0.266	2.717	6.338**
	LR (uncertainty)		−0.032	1.401**	0.209	2.769	3.049
SS (MRC)	LR (volatility)	Excluded	0.015	0.825*	0.012	0.366	0.458
	LR (recession)		0.039	0.542*	0.005	0.143	0.366
	LR (crisis)		−0.024	1.302**	0.172	1.436	1.554
	LR (illiquidity)		0.009	0.885**	0.237	1.290	5.542**
	LR (uncertainty)		−0.013	1.168**	0.182	2.437	2.690
SS (MRC)	LR (volatility)	Included	0.007	0.915*	0.015	0.487	0.553
	LR (recession)		0.037	0.554	0.004	0.182	0.372
	LR (crisis)		−0.019	1.246**	0.169	1.436	1.531
	LR (illiquidity)		0.011	0.869**	0.243	1.304	5.684**
	LR (uncertainty)		−0.007	1.098**	0.201	2.623	2.902
Alt. SS (MRC)	LR (volatility)	Included	−0.091**	1.591**	0.045	1.561	1.627
	LR (recession)		−0.005	0.537*	0.004	1.169	1.140
	LR (crisis)		−0.059**	1.198**	0.148	1.661	1.758
	LR (illiquidity)		−0.042**	0.977**	0.293	1.826	7.121**
	LR (uncertainty)		−0.056**	1.168**	0.218	3.116	3.388*
Panel B: BH benchmark							
STR (quadratic)	LR (volatility)	Excluded	0.036	0.698*	0.020	1.198	1.250
risk-adj. return	LR (recession)		0.056	0.523	0.009	1.444	1.191
	LR (crisis)		−0.002	1.028**	0.155	1.548	1.844
	LR (illiquidity)		0.029	0.755**	0.232	2.589	5.545**
	LR (uncertainty)		0.090**	0.227	0.006	1.714	1.165
SS (MRC)	LR (volatility)	Excluded	0.058*	0.497*	0.013	0.407	0.455
	LR (recession)		0.069*	0.404	0.006	0.324	0.440
	LR (crisis)		0.001	0.993**	0.187	1.546	1.604
	LR (illiquidity)		0.034**	0.702**	0.261	1.359	6.152**
	LR (uncertainty)		0.007	0.942**	0.142	2.079	2.256
SS (MRC)	LR (volatility)	Included	0.037*	0.502*	0.016	0.366	0.458
	LR (recession)		0.045*	0.404	0.005	0.360	0.479
	LR (crisis)		0.008	0.901**	0.202	1.671	1.722
	LR (illiquidity)		0.027**	0.631**	0.262	1.400	6.178**
	LR (uncertainty)		0.011	0.858**	0.164	2.308	2.513
Alt. SS (MRC)	LR (volatility)	Included	−0.037	0.962*	0.039	1.361	1.415
	LR (recession)		0.004	0.416*	0.003	1.132	0.918
	LR (crisis)		−0.039**	0.999**	0.159	1.605	1.703
	LR (illiquidity)		−0.029**	0.849**	0.303	1.771	7.374**
	LR (uncertainty)		−0.049**	1.134**	0.184	2.710	2.936

Notes: This table contains the estimated parameters and fits associated with an FMOLS regression of predicted risk-adjusted excess TTR returns (based on the expanding window updating method) as given by the STR (quadratic), SS (MRC), and alternative SS (MRC) models, on predicted risk-adjusted excess TTR returns (based on the expanding window updating method) as given by the LR (with dummy) model. Two test statistics associated with the null of no cointegrating relationship are provided: the Engle-Granger (EG) and Phillips-Ouliaris (PO) residual-based test statistics. These parameters and test statistics are provided for various benchmarks and dividend assumptions. Rejections of the null hypothesis that each parameter equals zero (or the null of no cointegrating relationship) at the 5% and 1% level are indicated by superscripts $*$ and $**$, respectively.

5.3. Factor-based tests

While the stochastic dominance tests provide useful insight into the performance of the TTR strategy (and are free from distributional assumptions), they are limited in that they do not incorporate potentially important forms of risk. To relax this assumption we estimate the LR (with a dummy variable to represent a particular market condition regime), STR (of various orders), and the SS (MRC and RWC) factor-based models described in Section 4.4.[25] The RF and BH benchmarks, and both short sales assumptions are considered. The estimated parameter values (key parameters only), significance indicators, and fit measures are presented in Table 4.[26]

The estimated parameters associated with the conventional LR (no dummy) factor model reveal a number of interesting features. First, the coefficients on the risk factors are generally very similar across models, but vary in sign and significance depending on the short sale assumption and the benchmark used. For instance, (somewhat unsurprising) the coefficient on the market premium factor is negative and significant when short sales are permitted (and/or when the BH benchmark is used), but positive when they are not (RF benchmark only). Second, regarding the intercept

[25] The parameters associated with all models are estimated using the Kalman filter algorithm under the Gaussian likelihood assumption in Eviews 8.

[26] Due to space limitations, a number of parameters are not presented. Most notably, the parameters within the transition function of the STR models are omitted. These are available on request.

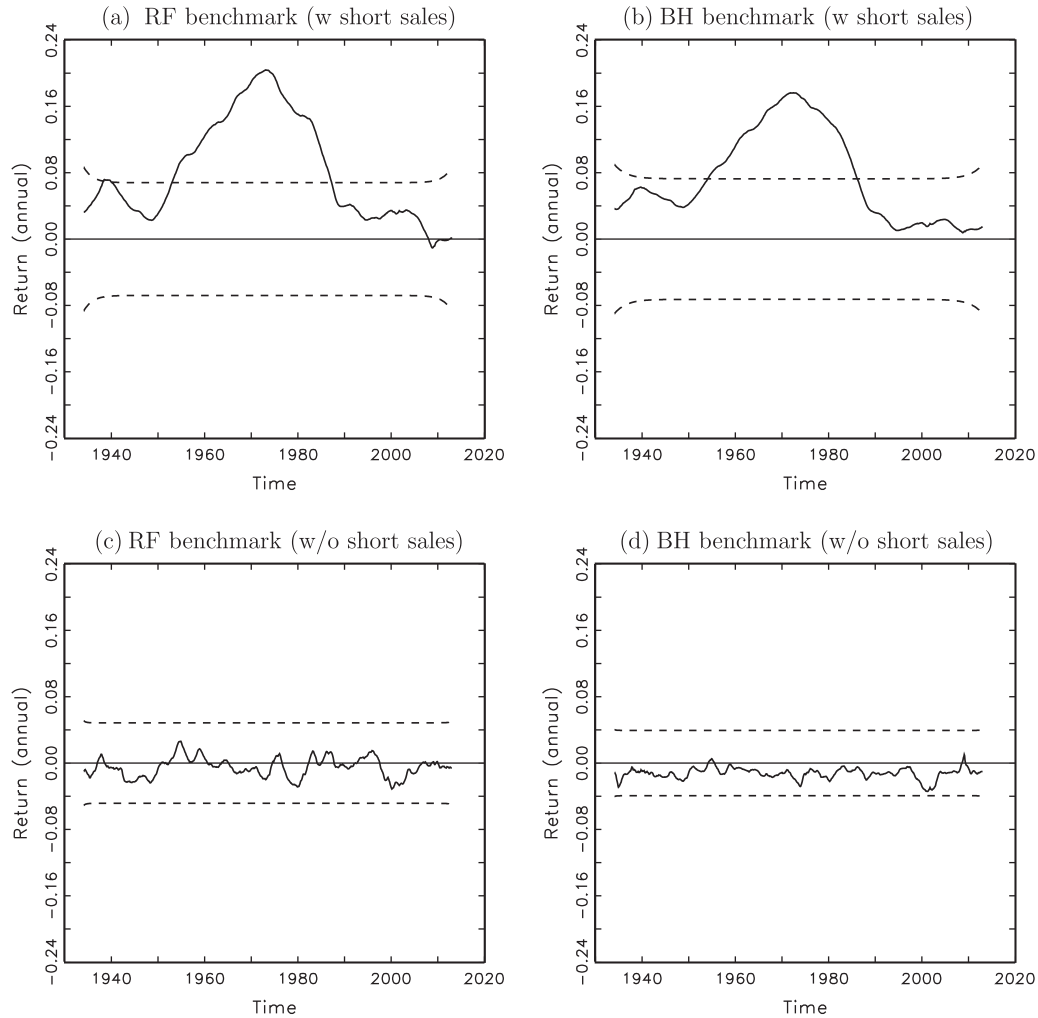

Fig. 5. Risk-adjusted excess returns (SS (MRC) model with dividends included). This figure contains the predicted risk-adjusted excess returns (and 95% confidence interval centred on zero) associated with the TTR portfolio (based on the expanding window updating method), two benchmarks, and two short sale assumptions. The predicted values are based on the SS (MRC) model. The individual stock returns used in the construction of the TTR and BH portfolio returns include dividend payments.

terms, the results indicate that significant positive risk-adjusted excess returns are possible only when short sales are permitted. For instance, when the RF benchmark is assumed, statistically significant risk-adjusted excess returns of 8.3% per annum exist. However, when the short sale restriction is imposed, risk-adjusted excess returns fall to −2.4% per annum.

The results associated with the LR (with dummy) factor models provide useful information regarding the impact of market conditions on risk-adjusted excess returns. In particular, risk-adjusted excess returns are significantly higher during recession periods (BH benchmark only), during economic/political crises (both benchmarks), during high market illiquidity periods (both benchmarks), and during high macroeconomic uncertainty periods (both benchmarks).[27] For instance, during the low market illiquidity period risk-adjusted excess returns equal 2.7% per annum (insignificantly different from zero), but are 10.4% per annum higher (significantly different from zero) during the high market illiquidity period. Moreover, the results reveal that this variation over market condition regimes is driven by short sales – as evinced by the insignificance of the dummy variable coefficients when short sales are not allowed.

Moving to the results associated with the STR and SS models, a number of findings are noteworthy. First, they provide a better fit to the data than the LR models when short sales are allowed, with the STR (quadratic) and SS (MRC) models appearing the best. By contrast, when the short sales restriction is imposed the best model is given by the LR (no dummy) model (irrespective of the benchmark used). Second, risk-adjusted excess returns in the STR regimes are significantly different from each other (both benchmarks, short sales allowed). For instance, when the RF benchmark is assumed, the STR (quadratic) model predicts statistically insignificant risk-adjusted excess returns of 2.2% per annum when the transition function equals zero. By contrast, these returns rise by 15.4% per annum when the transition function equals one. Finally, the SS (MRC) model appears best (both benchmarks, short sales allowed), with the parameter $\widehat{\phi}$ very close to one – indicating that risk-adjusted excess returns are highly persistent with a (near) unit root.

To obtain a feel for the nature of the time variation in risk-adjusted excess returns to the TTR strategy, the predicted risk-adjusted excess returns associated with the LR (with and without a dummy variable), the STR (quadratic), and SS (MRC) models are presented in Fig. 2 (RF benchmark, with short sales allowed) and

[27] The increase in TTR performance observed during recessions and economic/political crises is consistent with previous studies; see, e.g., Henkel et al. (2011), Kim et al. (2011), Han et al. (forthcoming), Neely et al. (forthcoming).

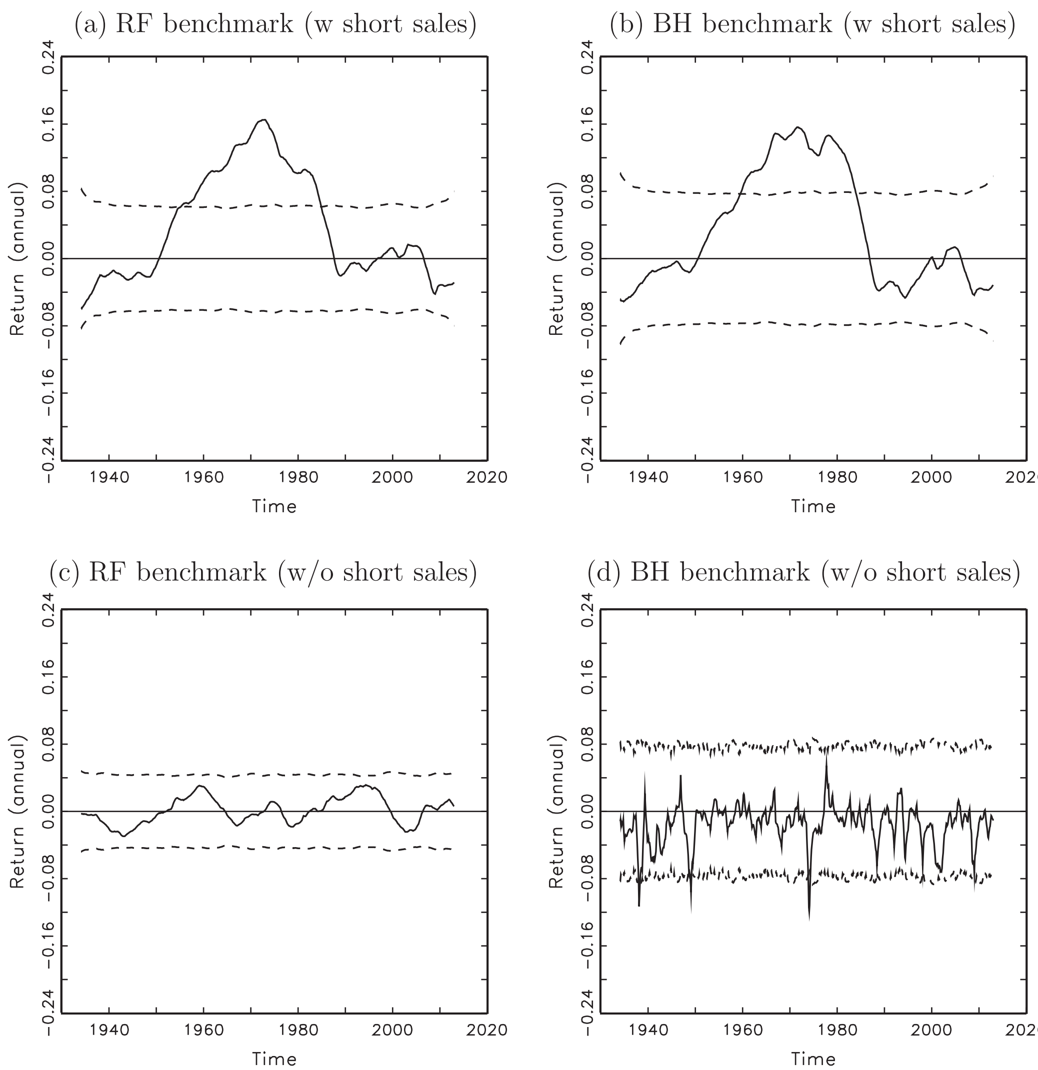

Fig. 6. Risk-adjusted excess returns (alternative SS (MRC) model with dividends included). This figure contains the predicted risk-adjusted excess returns (and 95% confidence interval centred on zero) associated with the TTR portfolio (based on the expanding window updating method), two benchmarks, and two short sale assumptions. The predicted values are based on the alternative SS (MRC) model in which the intercept and coefficient on the market premium are allowed to vary over time. The individual stock returns used in the construction of the TTR and BH portfolio returns include dividend payments.

Fig. 3 (BH benchmark, with short sales allowed). In addition, Fig. 4 provides plots of the predicted risk-adjusted excess returns (and 95% confidence intervals centred on zero) associated the SS (MRC) model under both benchmark and short sale assumptions.

The plots in Figs. 2 and 3 indicate that for the superior models (particularly the STR (quadratic) and SS (MRC) models), there appears to be an prolonged smooth increase in risk-adjusted excess returns during the 1960s, peaking during the early 1970s, and slowly decreasing to close to zero by the mid to late 1980s. A key observation is that this temporal variation has a strong low frequency component. The significance of the temporal variation in risk-adjusted excess returns can be seen in Fig. 4. The figure shows that there is a prolonged increase in risk-adjusted excess returns around the centre of the sample, with returns significantly above zero during this period when short sales are permitted. In all other periods, risk-adjusted returns are insignificantly different from zero. Moreover, when short sales are not allowed, risk-adjusted returns are less temporal and never significantly above zero.

5.4. The determinants of temporal variation

The previous analysis establishes that there is clear temporal variation in risk-adjusted excess returns to the TTR portfolio when short sales are allowed, that these evolve slowly (that is, they are persistent), and these are only significantly above zero during the centre of the sample (peaking during the early 1970s). However, this still leaves unresolved the issue of what determines this variation. We attempt to address this issue by assessing whether a particular market condition is best able to explain this variation. To this end we perform a series of regressions of the predicted risk-adjusted excess returns associated with the STR (quadratic) and SS (MRC) models upon those predicted by each of the LR (with dummy) models. As the results in Table 4 indicate that these predicted values follow (near) unit root processes, we conduct cointegration analysis based on the fully modified ordinary least squares (FMOLS) regression procedure proposed by Phillips and Hansen (1990). In addition, we examine the null of no cointegrating relationship using the parametric Engle-Granger, and nonparametric Phillips-Ouliaris residual-based tests.[28] Results are provided in Table 5.

The results indicate that the most likely determinants of TTR performance during the middle of the sample period are high market illiquidity, high macroeconomic uncertainty, or economic/

[28] The FMOLS regressions and associated cointegration tests are conducted using Eviews 8.

political crises. This is evinced by the significant values of the slope coefficient, and the relatively high adjusted R^2 values. Moreover, the cointegration test statistics indicate that one can reject the null of no cointegrating relationship when using the predicted risk-adjusted excess returns associated with the LR (with market illiquidity dummy variable) model. Thus, it would appear that the excellent TTR performance observed around the centre of the sample coincides with a prolonged period of high market illiquidity (see panel (e) in Figs. 2 and 3 for visual confirmation), and that this relationship is statistically significant.

5.5. Robustness checks

The robustness of the above results is examined by including cash dividends in the returns to each stock and by considering an alternative factor-based model.

5.5.1. The cash dividend assumption

To ensure consistency with the majority of previous studies (including BLL), the above analysis does not include cash dividends in the returns to each stock. However, this is potentially a serious omission as this will underestimate returns to the BH strategy, and tend to overestimate returns on short sales (Fama and Blume, 1966).[29] To investigate this issue we re-estimate the returns to all TTR and BH strategies using returns that include cash dividend payments. The plots pertaining to the risk-adjusted excess returns to the TTR portfolio based on the SS (MRC) model, under the RF and BH benchmarks and both short sale assumptions, are provided in Fig. 5. In addition, the cointegrating regressions described in Section 5.4 are re-estimated using these data, with results presented in Table 5.

The evidence in these plots suggests that the results are largely robust to the cash dividend assumption. In particular, the main findings still hold: risk-adjusted excess returns to the TTR portfolio are significantly above zero around the centre of the sample, and short sale ability has an enormous impact on performance. As one would expect, the only difference occurs when the BH benchmark is used, with risk-adjusted excess returns uniformly lower by around 2–4% per annum – a small reduction in comparison to the risk-adjusted excess returns of around 25% per annum observed during the peak period. Moreover, the results in Table 5 are largely unaffected with market illiquidity (and to a lesser extent macroeconomic uncertainty) the likely drivers of the observed temporal variation.

5.5.2. The factor-based model assumption

It could be argued that the above results are driven by use of a SS model in which the factor loadings are assumed to remain fixed over time. Indeed, it is quite possible that these loadings may actually change during the sample period to yield insignificant risk-adjusted excess returns. To address this issue we consider an alternative single factor model in which the factor loading on the market premium is allowed to vary over time. In particular, the following alternative SS (MRC) model is considered:

$$Y_t = \alpha_t + \beta_t Z_t + \epsilon_t, \quad \epsilon_t \sim \mathrm{NID}(0, \sigma_\epsilon^2), \tag{13a}$$

$$(\alpha_{t+1} - c_0) = \phi_\alpha(\alpha_t - c_0) + \eta_t, \quad \eta_t \sim \mathrm{NID}(0, \sigma_\eta^2), \tag{13b}$$

$$(\beta_{t+1} - d_0) = \phi_\beta(\beta_t - d_0) + \xi_t, \quad \xi_t \sim \mathrm{NID}(0, \sigma_\xi^2). \tag{13c}$$

This model is estimated using the RF and BH benchmarks, and both short sale assumptions.[30] The estimates of α_{t+1} (and associated 95% confidence intervals centred on zero) are provided in Fig. 6, while the estimated parameters associated with the cointegrating regressions described in Section 5.4 are provided in Table 5.

The plots confirm the findings associated with the previously considered SS (MRC) model. In particular, there appears to be a prolonged increase in risk-adjusted excess returns to the TTR portfolio around the centre of the sample, with returns significantly above zero during this period when short sales are permitted. In all other periods, risk-adjusted returns are insignificantly different from zero. Moreover, when short sales are not allowed, risk-adjusted returns are less temporal and never significantly above zero. Moreover, the results in Table 5 confirm that market illiquidity is the most likely cause of the observed temporal variation in risk-adjusted excess returns to the TTR portfolio.

6. Conclusions

The results in this paper provide further insight into the nature of the profits available to users of two sets of important momentum-based TTRs. There are three defining features: risk-adjusted profits are confined to the period from around the mid-1960s to the mid-1980s, peaking during the early 1970s; profits coincide with a period of high market illiquidity (and to a lesser extent high macroeconomic uncertainty), and profits are only available to investors who can conduct short sales in stocks. For all other investors, no risk-adjusted profits are available. However, it should be noted that as a finite number of TTRs are applied to a small group of highly traded equities, these features are not necessarily generalisable outside of this group.

The temporal variation in risk-adjusted excess returns to the TTR portfolio has a strong low frequency component. Consequently, it is perhaps no surprise that market conditions with a short to medium frequency component such as those driven by market volatility or the business cycle are unlikely to provide a convincing explanation for variation in TTR performance. In particular, they are unlikely to be able to explain why TTR profits are confined to the pre-BLL sample period; see, e.g., Henkel et al. (2011) for empirical evidence that the uneven distribution of recessions over time cannot explain the disappearance of predictability in the post 1991 period. Rather, it seems that these profits are driven by a low frequency change in market illiquidity over time.

The findings are consistent with the adaptive market hypothesis proposed by Lo (2004), in that TTR performance is temporal with prolonged periods of success and failure. Thus the findings could be indicative of increasing interest (and usage) of TTRs when market conditions allow – in this instance, these conditions coincide with periods of high market illiquidity, and to a lesser extent high macroeconomic uncertainty. It is quite possible that this, in turn, sparked a renewed interest in such strategies and ultimately drove profits back down to zero.

There is an additional dimension to the performance of TTRs not previously documented. In particular, the temporal success of TTRs is driven by the ability to short-sell stocks. This raises an additional interpretation of the results that is more closely related to Jensen (1978) notion of market efficiency. In particular, it could be the case that the cost of short-selling stocks (or the perceived risk thereof) during periods of TTR success was so high that the marginal costs exceeded the marginal benefits (profits) of trading – perhaps evinced by the high market illiquidity observed during these periods. In the current absence of any data pertaining to short-selling costs over the entire sample period considered, this issue is left for future work.[31]

[29] Bessembinder and Chan (1998) demonstrate that the BLL results are significantly affected by, inter alia, the inclusion of cash dividends.

[30] The parameters are estimated using the Kalman filter algorithm under the Gaussian likelihood assumption in Eviews 8. Parameter estimates are available on request.

[31] Short sale costs are available over other periods; see Jones and Lamont (2002) for prewar evidence, D'Avolio (2002) for evidence of a fairly recent vintage, and Kolasinski et al. (2013) for evidence pertaining to the recent financial crisis.

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