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Limits to Arbitrage and Value Investing: Evidence From Brazil

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ABSTRACT. *In this article we show that the results obtained by accounting-based fundamental analysis strategies observed in the US market cannot be directly extended to emerging markets with less developed institutional environments and narrow equity markets as found in Latin America. We use Brazil as a special case and through standard tests show the apparent usefulness of financial statement analysis as an effective investment tool. We show that an investor could have changed his/her high book-to-market (HBM) portfolio one-year (two years) market-adjusted returns from 5.7% (42.4%) to 26.7% (120.2%) by selecting financially strong HBM firms listed on the São Paulo Stock Exchange. Our tests were performed using stock returns from 1995 to 2007 and financial and accounting data from 1994 to 2004. When one considers low book-to-market (LBM) firms, the results of the study indicate that an investor could change his/her mean (median) one-year market adjusted return from −11.9% (−7.4%) to 8.1% (2.5%) by adopting the strategy proposed. However, additional investigation demonstrates that the returns generated by these strategies are significantly dependent on stock's liquidity, and when we consider only stocks where arbitrage is possible, the previous results do not hold. These findings contribute to the literature that tries to address the impact of limits to arbitrage on some well reported capital markets phenomena related to financial reporting.*

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RESUMEN. *En este artículo se demuestra que los resultados obtenidos con las estrategias de inversión en análisis fundamentalista, observados en el mercado norteamericano, no pueden aplicarse directamente en los mercados emergentes que tengan un entorno institucional menos desarrollado y mercados de valores más robustos, como los existentes en Latinoamérica. Utilizando a Brasil como un caso especial, vemos que las pruebas estándar muestran que la aparente utilidad de los análisis fundamentalistas es una herramienta de inversión eficaz. También mostramos que el inversor en el mercado brasileño (Bovespa) podría cambiar sus retornos ajustados por el mercado en un portfolio de empresas 'high book-to-market' (HBM) y con buena saludad financiera, del 5,7% (42,4%) para 26,7% (120,2%) en un año (dos años), Elaboramos nuestras pruebas tomando en consideración el retorno que las acciones obtuvieron entre 1995 y 2007, así como los datos contables y financieros entre 1994 y 2004. Al considerar a las empresas con bajo valor contable-valor de mercado (LBM), los resultados de la estrategia indican que un inversor cambiaría en un año su retorno medio ajustado al mercado de 11,9% (−7,4%) para 8,1% (2,5%) en un año (dos años). No obstante, otras investigaciones muestran que el retorno generado por dichas estrategias depende significativamente de la liquidez de las acciones y que, si se consideran apenas las acciones que pueden llegar a un arbitraje, los resultados anteriores no se mantendrían. Estos hallazgos brindan una contribución a la literatura que intenta abarcar el impacto que los límites del arbitraje tienen sobre algunos fenómenos de los mercados de capitales bien reportados, relativos a los informes financieros.*

RESUMO. *O presente artigo demonstra que os resultados obtidos com as estratégias de investimento baseadas em análise fundamentalista observados no mercado norte-americano, não podem ser estendidos diretamente à mercados emergentes que tenham um ambiente institucional menos desenvolvido e com mercado de capitais menos pujantes, como os encontrados na América Latina. Neste artigo, o Brasil foi investigado como um caso especial e os testes padrão mostram a utilidade aparente da análise fundamentalista como uma eficaz ferramenta de investimentos. Os resultados mostram que um investidor no mercado brasileiro (Bovespa) poderia ter alterado o seus retornos ajustados pelo mercado em um portfólio de empresas high book-to-market (HBM) e com boa saúde financeira, de 5,7% (42,4%) para 26,7% (120,2%) em um ano (dois anos). Os testes foram realizados levando em conta o retorno das ações de 1995 a 2007, e também os dados contábeis e* *financeiros de 1994 a 2004. Na avaliação de empresas com baixo PL/P (empresas LBM), os resultados da estratégia indicam que um investidor poderia mudar o seu retorno médio ajustado ao mercado, de 11,9% (−7,4%) para 8,1% (2,5%) em um ano (dois anos). Contudo, análises adicionais mostram que o retorno gerado por essas estratégias depende significativamente da liquidez das ações, e se forem consideradas apenas ações para as quais há a possibilidade de arbitragem, os resultados prévios não são mantidos. Estes resultados contribuem para a literatura que tenta avaliar o impacto dos limites de arbitragem em alguns fenômenos bem relatados do mercado de capitais.*

KEYWORDS. *emerging markets, financial statement analysis, limits to arbitrage, market efficiency, value investing*

INTRODUCTION

In this article we try to shed some light on the determinants of the abnormal returns (i.e., returns above the value-weighted market return) generated by accounting-based fundamental analysis strategies (or financial statement analysis—FSA hereafter) using specific data found in a developing equity market, where arbitrage mechanisms are formally present[1] but in practice can be applied only to some extremely liquid stocks. We address an essential question: Why do arbitrageurs not drive away FSA-related mispricing? Previous research (Piotroski, 2000; Mohanram, 2005) has shown that one can obtain returns in excess of the market-adjusted expected rate by buying (selling) strong (weak) firms. They argue that these results are a function of two factors: (i) informative accounting reports and (ii) some inefficiency in the price formation process. For FSA to be effective, one needs financial statements to be useful and also either be ignored (the Piotroski story for value firms) or misinterpreted (the Mohanram story for growth firms) by users. The basic point is that the returns to FSA are potentially determined jointly by the inherent usefulness of financial statement information and the extent to which this information is incorporated in a timely fashion into stock prices.

In this article, we try a direct approach to measure the whether arbitrage is possible on FSA strategy returns. We investigate the returns to FSA in markets where we can directly address the two sources commented on by Mashruwala, Rajgopal, and Shevlin (2006). Our main hypothesis is that abnormal returns to FSA in a market like Brazil will be influenced by limits to arbitrage. We expect that after a proper control for restrictions on the actions of arbitrageurs, excess returns to FSA will be significantly reduced. We use the São Paulo Stock Exchange in Brazil (BM&FBOVESPA) to investigate this hypothesis.

Brazil possesses several limitations imposed on arbitrageurs that make it possible to separate stocks that can from those that cannot be arbitraged. The average trading volume for high book-to-market (HBM) Brazilian firms during our sample period was below US $300,000 per day and the bid and ask spreads were high. Low levels of liquidity combined with transaction restrictions are important when implementing a long-short trading strategy in an emerging market like Brazil. Second, short sales are not generally allowed. This has an important implication for the long-short strategies analyzed by Piotroski (2000) and Mohanram (2005). At BM&FBOVESPA, if a market participant wants to bet on the downside risk he or she has to borrow the share and sell it with a commitment to buy back in the future. Such transactions are unlikely to occur for most shares because liquidity can make the buyback transaction impossible. Third, due to liquidity problems and the low number of shares traded on BM&FBOVESPA, similar assets are not available in Brazil. Traders cannot buy the illiquid shares and sell the stock index because the BM&FBOVESPA stock index is built on the most liquid shares. Derivatives are not available for these shares because BM&FBOVESPA does not list derivatives on such illiquid underlying. In summary, a short-sell in Brazil can only be implemented when an investor can borrow the stock. Stocks that do not make up the IBOVESPA (São Paulo Exchange Stock Index) can hardly be borrowed. This makes a short-sell strategy virtually impossible when considering shares that do not make up the IBOVESPA.

Thus, if returns to fundamental analysis are influenced by restrictions to arbitrage we expect these returns to be abnormally high in Brazil. Additionally, we expect that when controlling for situations where short-selling is not possible (i.e., there are restrictions to arbitrage), these abnormal returns will be driven away.

To test our hypothesis we first replicate an adapted version of Piotroski (2000)—for the sake of comparability—creating the *BrF_SCORE,* which reflects the firms' financial position. Second, we implement a simplified version of Mohanran's (2005) strategy, creating *BrG_SCORE*. In both strategies we specifically analyze the impacts of restrictions to arbitrage.

The implementation of the *BrF_SCORE* strategy shows that an investor could have changed his or her HBM portfolio one-year (two-year) market-adjusted returns from 5.7% (42.4%) to 26.7% (120.2%) by selecting financially strong HBM firms during the 1994–2004 period on the São Paulo Stock Exchange (BM&FBOVESPA). Our results are considerably higher than Piotroski's (2000), who increased his portfolio one-year (two-year) market adjusted return from 5.9% (12.7%) to 13.4% (28.7%). Additionally, a strategy based on forming portfolios long on financially strong HBM firms and short on financially weak HBM firms generates 41.8% annual (or 144.2% for two cumulative years) market-adjusted returns between 1994 and 2004. Again our portfolio returns are higher than Piotroski (2000), who found 23% annual or 43% for two cumulative years. These results confirm our hypothesis that fundamental value strategies generate significantly higher returns in Brazil than in the United States.

However, after partitioning the sample, our results show that the fundamental analysis strategy employed works only for the groups of small- and medium-sized firms and for the groups of low and medium liquidity firms but not for the group of large size and high liquidity firms. Basically, our results only hold for the group of shares with more severe limits to arbitrage due to low liquidity. Low liquidity is a proxy for limits to trade and to arbitrage.

To avoid controversy over the adequate proxies to control for limits to arbitrage we use a different control for restrictions on the actions of arbitrageurs in Brazil. We select only the shares for which arbitrage is possible: shares that allow traders to sell short without liquidity concerns and that are part of the stock index. Using pooled and panel data specifications we show that *BrF_SCORE* is not statistically related to abnormal returns for these firms. *BrF_SCORE* explains returns for the full sample but not for the subsample of firms for which arbitrage is possible.

To check the robustness of our results we have also tested an adapted version of GSCORE (Mohanram, 2005), called *BrG_SCORE*, on the sample of low book-to-market (LBM) firms. Results show that the short-long strategy for LBM also differentiates between ex-post winners and losers. Firms with the highest *BrG_SCORE* earned a mean market-adjusted return of 8.1% (6.8%) in the first (second) year after portfolio formation, while firms with the lowest *BrG_SCORE* generated –34.5% (–31.8), indicating that a long–short strategy based on *BrG_SCORE* can earn significant abnormal returns. However, when partitioning the results obtained by *BrG_SCORE* strategy, we identified that the excess returns are reduced when arbitrage is possible (i.e., when one considers high liquidity stocks).

Our results contribute to a recent strand of the literature that tries to address the impact of limits to arbitrage on some well-reported capital markets phenomena related to financial reporting. Mashruwala and colleagues (2006) explained the accrual anomaly based on the same "limits to arbitrage" argument used here. Cohen, Dey, Lys, and Sunder (2007) showed that the earnings announcement premiums are not completely eliminated due to the costs of arbitrage; Frazzini and Lamont (2006) found similar results while controlling for liquidity. We contribute by addressing the effect of limits to arbitrage on the results of accounting-based fundamental analysis.

The rest of the article is organized as follows. Section 2 reviews prior research on the book-to-market effect, fundamental analysis, and motivates the article. Section 3 presents the main features of Brazilian capital markets and accounting information. Section 4 presents the financial performance signals used to identify strong and weak HBM firms. Sample selection, summary statistics, and results are presented in Section 5. Section 6 concludes the article.

LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

The ability to earn abnormal returns based on the use of financial statements receives significant attention from researchers. Ou and Penman (1989) used financial statement analysis and document that a set of financial ratios are able to forecast future earnings and stock returns. Lev and Thiagarajan (1993) analyzed financial signals that are frequently used by analysts, and showed that these signals are correlated to returns. Abarbanell and Bushee (1997) documented that an investment strategy based on financial signals help investors to earn significant abnormal returns. Concerning specific accounting signals, Sloan (1996) found evidence that firms with higher amounts of accruals underperform in the future. Piotroski (2000) related the HBM effect to financial statement analysis and showed that the mean return earned by a HBM investor can be increased by at least 7.5% annually through the selection of financially strong HBM firms. Beneish, Lee, and Tarpley (2001) used market-based signals and financial statement analysis to differentiate between winners and losers. Mohanram (2005) combined traditional fundamental analysis with measures tailored for LBM firms and documents significant excess returns.

It is important to note that previous research (Piotroski, 2000; Mohanram, 2005) has shown that significant abnormal returns are generated by trading strategies based on the analysis of financial statements in the United States. They argue that this market does not completely reflect the information contained in financial statements and consequently that it is possible to earn abnormal returns by buying (selling) financially strong (weak) firms. Summarizing, this literature suggests that prices are not fully efficient regarding accounting reports (even in more efficient markets) and recommends strategies based on financial reports designed to explore such mispricing.[2]

However, a recent branch of the financial economics literature (the so-called behavioral finance) argues that price deviations from fundamentals can persist in the long run because arbitrage is not as easy a process as the traditional efficient market hypothesis (EMH) assumes (Shleifer, 2000; Shleifer & Vishny, 1997). These authors argue that arbitrage can be costly, risky, and sometimes even impossible due to market restrictions to trade. Arbitrage is a central concept in the EMH formulation—without arbitrage there is no EMH and prices can deviate from fundamentals and consequently abnormal returns can be achieved using public information. Very recently the accounting literature started to investigate some well-known accounting-related anomalies in the light of the restriction to arbitrage theories. Mashruwala and colleagues (2006) stated that the so-called accrual anomaly (Sloan, 1996) is caused by transaction costs and that arbitrageurs do not correct the accrual anomaly because of transaction costs, low liquidity, and high idiosyncratic risk. Cohen and associates (2007) showed evidence that the abnormal returns observed around earnings announcements—long reported by the accounting literature

(Ball & Kothari, 1991; Penman, 1984)—are not arbitrated due to high costs. Recently, Wahlen and Wieland (2011) found that investors can earn greater returns by ignoring analysts' stock recommendations and picking stocks simply using financial statement information that predicts future earnings increases. However, when analyzing the results of what they have called *fundamental strategy* (i.e., abnormal returns an investor could expect to generate by relying solely on financial statement analysis within each consensus recommendation category), one realizes that when controlling for long and short positions, only the long position strategy is significant.

In this article we contribute to this literature by investigating excess returns to FSA in an emerging market where accounting reports are not supposed to be as informative as in the United States and these returns are likely to be driven by limits to arbitrage (Cohen et al. 2007; Mashruwala et al. 2006). More specifically, we suspect that Piotroski (2000) and Mohanram's (2005) results cannot be completely extended when arbitrage is directly controlled. We argue this because Piotroski's results are mainly driven by small and less liquid firms and Mohanram's results are very hard to implement in real markets as Piotroski (2005) argued. For example, Mohanram's (2005) results are smaller for firms with put options; this suggests that impediments to hedging influence the results. Additionally, there is a significant body of literature that shows that abnormal returns are influenced by liquidity and limitations to arbitrage (Bekaert, Harvey, & Lundblad, 2006). Based on this literature, in this article we try to complement the Mohanram (2005) and Piotroski (2000) papers and uncover the determinants of the mispricing reported. Our main hypothesis is that the excess returns generated by FSA will be the result of limits to trade unlike Piotroski (2000) and Mohanram (2005). In the next section we show why Brazil provides a unique opportunity to investigate this question.

WHY BRAZIL? CAPITAL MARKETS AND LIMITS TO ARBITRAGE

To investigate whether abnormal returns to fundamental analysis are driven mainly by limits to trade we need a setting with strict restrictions on trade and consequently to arbitrage. We believe Brazil provides this opportunity because arbitrage is difficult for most HBM firms due to illiquidity, restrictions to short sales, and the absence of similar assets like derivatives for such shares.

For markets to be efficient a key element is necessary: arbitrage. Arbitrage is the mechanism by which information is incorporated into prices. For the market to be efficient, it is not necessary for all agents to be rational or to have the same amount of information. As long as arbitrage is possible prices are driven to fundamentals by the actions of traders with superior information (Shleifer, 2000). For arbitrage to be achievable in real markets, a series of conditions must be in place. Initially, the market must have enough liquidity to accommodate the trading orders of such investors. This can easily become a problem because arbitrageurs can trade on huge sums on behalf of mutual funds, pension funds, and banks. Second, similar assets must be available to allow for arbitrage to be feasible. Arbitrage strategies frequently consist of buying a given asset and selling a similar one. Third, short sales or other similar mechanisms like derivatives must be available to allow traders to bet on the downside risk. These features must be available on a continuous basis and not only sporadically for arbitrageurs to be able to engage in such strategies.

There is pervasive evidence that Brazilian capital markets impose several restrictions on the actions of arbitrageurs, especially for HBM firms. Recently, Chong and López-de-Silanes (2007b) showed that this is actually the case for most of Latin America. Initially, these shares trade at very low volumes that restrict some institutions to trade—especially pension funds, hedge funds, large banks, and mutual funds that are more specialized and likely to correct market inefficiencies. The average monthly stock cash volume traded in Brazil is considerably lower than in the United States. The mean (median) average monthly dollar amount traded per stock in Brazil at BM&FBovespawas was USD $11,304,407 (USD $50,654) and in the United States at NYSE, AMEX, and NASDAQ was USD $233,799,937 (USD $13,473,605) during our sample period.[3] In 1994, BM&FBovespa had 211 firms with actively traded stocks (usually these firms were considered "big-sized" firms for the Brazilian market). From 1994 to 2006, 54 new firms listed at BM&FBovespa. Additionally some of these newly listed firms were considerably smaller than the previously listed companies.[4] This liquidity problem has some important consequences for another condition essential to arbitrage: the presence of similar securities. HBM shares in Brazil do not integrate with the São Paulo Stock Exchange Index that only accounts for the approximately 60 most liquid shares and are not underlying for derivative financial instruments—the stock exchange will not list derivatives based on illiquid shares. Thus, arbitrageurs in Brazil face low liquidity and the absence of similar assets. Additionally, short sales are not allowed in Brazil. To sell a share short a trader must borrow it and sell in t_0 and then buy it back in t_1. On an illiquid market this strategy is very risky because there is no guarantee that one will be able to buy the share back in t_1.

RESEARCH DESIGN

We consider the research design of Piotroski (2000) and Mohanram (2005) to build adapted versions of *FSCORE* and *GSCORE*. Initially we apply an adapted version of the strategy proposed by Piotroski (2000), who built a score composed of fundamental signals extracted from financial statements.

These variables are intended to be useful in predicting future firm performance, especially the financially distressed ones (HBM). We use the nine basic fundamentals signs identified by Piotroski (2000), making some adaptations due to the features of Brazilian accounting information and capital markets. We classify each firm's signal realization as either "good" or "bad" depending on the signal's theoretical impact on future prices and performance. If the realization signal is "good" the indicator variable is equal to one (1); if it is "bad," it equals zero (0). The main reason for us adapting Piotroski's score is the absence of published cash flow statements in Brazil.

The three financial signals used to measure changes in capital structure and liquidity are *CF*, Δ*LIQUID*, Δ*LEVER*, and *EQ_OFFER*. As stated by Piotroski (2000, p. 2), since most HBM firms are financially distressed we assume that increases in leverage, weakening in liquidity, or public offerings of equity are "bad" signals. *CF* is defined by the firm-year change in cash and cash equivalents scaled by beginning-of-the-year total assets. This is the main difference between our score (*Br_FSCORE*) and Piotroski's *F_SCORE*. Δ*LIQUID* measures the changes in firm's current ratio in relation to previous year. The current ratio is defined as the ratio of current assets to current liabilities at company's year-end. An improvement in liquidity represents $\Delta LIQUID > 0$ and is considered a "good" signal, "bad" otherwise. The change in firm's gross debt level is represented by Δ*LEVER*. We measure Δ*LEVER* as the change in the ratio of total gross debt to total assets in relation to the prior year. An increase in leverage ($\Delta LEVER > 0$) is a "bad" signal while a decrease is "good." The variable *EQ_OFFER* represents the use of equity financing. If the firm did not issue equity[5] in the year preceding portfolio construction it is a "good" signal (*EQ_OFFER* equals one), "bad" (*EQ_OFFER* equals zero) otherwise.

The three variables used to measure profitability are *ROA*, Δ*ROA*, and *ACCRUAL*. *ROA* is defined as net income scaled by beginning-of-the-year total assets.[6] We considered positive *ROA* as "good" information, "bad" otherwise. We define Δ*ROA* as the current firm-year *ROA* less the previous firm-year *ROA*. If *ROA* changes is positive it is considered a "good" signal, if not it is considered a "bad" signal. We define *ACCRUAL* as changes on noncash current assets minus changes on current liabilities (except short-term debt) minus depreciation, scaled by beginning-of-the-year total assets. The indicator variable (*F_ACCRUAL*) equals one ("good") if $CF > ROA$, zero ("bad") otherwise. This treatment is consistent with Sloan (1996) and shows that a great amount of accruals into earnings is a bad signal for future performance.

Operating efficiency is measured by Δ*MARGIN* and Δ*TURN*. We define Δ*MARGIN* as the change in firm-year current gross margin scaled by total sales (gross margin ratio) compared to the previous year. A positive change (i.e., $\Delta MARGIN > 0$) means a "good" signal, while a negative change is classified as "bad." Finally, we define Δ*TURN* as the change in firm's current firm-year sales scaled by beginning-of-the-year total assets (asset turnover ratio). An improvement in assets turnover is a “good” signal, thus indicator variable (*F*_D*TURN*) equals to one, or zero otherwise.

The composite score represents the sum of the following indicator variables, or:

$$BrF\_SCORE = F\_ROA + F\_CF + F\_\Delta ROA + F\_ACCRUAL + F\_\Delta LIQUID + F\_\Delta LEVER + EQ\_OFFER + F\_\Delta MARGIN + F\_\ \Delta TURN.$$

BrF_SCORE range is from 0 (“bad” signals) to 9 (“good” signals). Low *BrF_SCORE* represent firms with poor expected future performance and stock returns, while high *BrF_SCORE* is associated with firms expected to outperform. The investment strategy analyzed in this article is similar to Piotroski (2000) and is based on selecting firms with high *BrFscore*. We consider firms with high *BrF_SCORE* the ones in the range of 7 to 9 and firms with low *BrF_SCORE* the ones beneath or equal to 3. We expand the range in comparison to Piotroski (2000) due to the sample size and to special features of Brazilian capital markets (e.g., the low number of equity offerings during our sample period). The idea behind *BrF_SCORE* is to create a simplified proxy to capture fundamental signals usually explored by equity analysts. *BrF_SCORE* attempts to translate profitability, liquidity, capital structure, and operating efficiency measures into binary codes in a way that is simple and easy to implement. The higher *BrF_SCORE* the stronger are the financial signals from the firm.

To check the validity of our results using the sample of LBM firms we also build an adapted version of GSCORE (Mohanram, 2005) from 1994 to 2004. We consider the sum of eight signs (G1:G8) that have a default value of 0 and equal 1 if the following criteria are met: G1: ROA ≥ industry median, G2: CF ≥ industry median, G3: CF ≥ ROA, G4: Δ%ROA ≤ industry median, G5: Δ%GSAL ≤ industry median, G6: DefAINT ≥ industry median, G7: CAPINT ≥ industry median, G8: SINT ≥ industry median. ROA is net income scaled by average assets. CF is change in cash scaled by average assets. Δ%ROA and Δ%GSAL are the percentage growth of ROA and sales respectively measured over the last year. Deferred Assets is deferred assets scaled by total assets. Capex is capital expenditure scaled by total assets. Sales expense is selling expenses divided by total assets. Industry medians are calculated at the level one NAICS within LBM firms. The composite score for LBM firms represents the sum of the eight indicator variables, or: $BrG\_SCORE = \sum_{i=1}^{8} G_i$.

SAMPLE SELECTION AND RESULTS

Sample Selection

We start with all nonfinancial firms listed in BM&FBovespa between January 1, 1994 to December 31, 2007.[7] We collect this data from the Economatica®

database and we select the higher liquidity stock class[8] of each firm for each year. This procedure resulted in 6682 firm-year observations. Additionally we identify firms with sufficient stock prices and book values and calculate the market value of equity (*MVE*) and book-to-market ratio (*BM*) of each company at fiscal year-end. We calculate *BM* as the book value at fiscal year-end divided by the market value of equity at the same date represented by the balance sheet. Finally we exclude firms with negative *BM* and trimmed the data at 1% for one-year-raw returns. Companies with sufficient data are annually classified and we identify the distributions of *BM* and *MVE*. This procedure resulted in 2151 firm-year observations.

We use the *BM* distribution from the prior year to the construction of the portfolio and classify firms *BM* data for each year into *BM* quintiles. To construct the HBM portfolio (value firms) we selected the top *BM* quintile, while the LBM firms are represented by the first quintile. Additionally we separate companies by size (small, medium, or large) according to their 33.3 and 66.7 percentiles distribution of *MVE* and by their stock liquidity (low, medium, or high) according to their 33.3 and 66.7 percentiles distribution of stock liquidity ratio. This approach results in 426 HBM firms in the final sample from 1994–2004.

Returns

Firm returns are calculated as buy-and-hold returns for one-years and two-years starting on the 1st of May of the year after portfolio formation. This procedure is the same as the one used by Piotroski (2000) and Mohanram (2005) to ensure all financial statements were publicly available at the moment of portfolio formation. This method is consistent with Brazilian requirements for publicly held companies to release their annual financial statements by the end of April. If a firm delists, we consider returns until the delisting date and assume no delisting return. We define market-adjusted-returns as the buy-and-hold returns for one-year and two-years in excess to the value-weighted market return[9] over the same time period.

Results

Table 1 panel A, B, C, and D presents the buy-and-hold returns for the investment strategy based on financial statement analysis for the HBM portfolio of Brazilian firms. We present the mean, median, and percentiles one-year raw, one-year adjusted, two-years raw and two-years adjusted returns for each *BrF_SCORE* class. We test the returns earned with high *BrF_SCORE* firm portfolios against returns gained from low *BrF_SCORE* firm portfolios. We adopted a two-sample mean comparison test for mean returns, two-sample proportion test for positive returns, and Wilcoxon signed-rank test for median returns. Additionally we implement the bootstrap procedure to

TABLE 1 Buy-and-Hold Returns to a Value Investment Strategy Based on Fundamental Signals

Panels A, B, C, and D present the buy-and-hold returns to financial statements analysis based on fundamental signals of high book-to-market firms. Low BrF_SCORE portfolio consists of firms with aggregate scores of 1–3 while the High BrF_SCORE consists of firms with scores of 7–9.

Panel A: One-Year Raw Returns

Returns	Mean	10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile	%Positive Signal	N
All Firms	0.3569	–0.4815	–0.2427	0.1192	0.7453	1.5180	0.5634	426
BrF_SCORE								
1	0.0317	–0.1818	–0.1818	0.0317	0.2451	0.2451	0.5000	2
2	0.1094	–0.5474	–0.3278	0.0847	0.4645	0.8275	0.5333	30
3	0.2287	–0.6002	–0.3590	–0.0400	0.5000	1.5000	0.4490	49
4	0.4260	–0.4783	–0.1957	0.2580	0.8551	1.5472	0.5921	76
5	0.2263	–0.5231	–0.3797	–0.0262	0.5779	1.3768	0.4651	86
6	0.3997	–0.4917	–0.2196	0.2059	0.7958	1.7963	0.6477	88
7	0.6427	–0.4111	–0.1354	0.2265	1.3361	2.0000	0.6610	59
8	0.3242	–0.3248	–0.1852	0.1912	0.7059	1.2973	0.6296	27
9	0.4226	–0.4050	–0.2873	–0.1367	0.4349	3.1018	0.3333	9
Low Score (1–3)	0.1797	–0.5717	–0.3333	0.0000	0.4645	1.1053	0.4815	81
High Score (7–9)	0.5314	–0.4000	–0.1821	0.2040	0.9500	1.7671	0.6211	95
High–Low	0.3517	0.1717	0.1512	0.2040	0.4855	0.6618	0.1396	–
t-stat/z-stat (*p*-Value)	2.6943	–	–	2.723	–	–	1.8578	–
	(0.0077)	–	–	(0.0065)	–	–	(0.0632)	–
Bootstrap Result								
1000 rep/z-stat	2.7300	–	–	2.8600	–	–	–	–
(*p*-Value)	(0.0060)	–	–	(0.0040)	–	–	–	–

Panel B: One-Year Market Adjusted Returns

Returns	Mean	10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile	%Positive Signal	N
All Firms	0.0574	–0.8279	–0.5194	–0.1220	0.3903	1.2739	0.4460	426
BrF_SCORE								

1	−0.3430	−0.8949	−0.8949	−0.3430	0.2089	0.2089	0.5000	2
2	−0.2474	−1.1028	−0.6231	−0.3935	0.2718	0.5957	0.4333	30
3	−0.0845	−1.1481	−0.6115	−0.2131	0.2158	1.0972	0.3469	49
4	0.1533	−0.6214	−0.3988	−0.0209	0.4917	1.3832	0.4868	76
5	−0.1017	−0.8865	−0.5991	−0.2281	0.2026	0.9439	0.3256	86
6	0.0962	−0.8541	−0.5322	0.0113	0.4392	1.4155	0.5114	88
7	0.3862	−0.5541	−0.2701	0.1372	1.0540	1.6199	0.5593	59
8	0.0771	−0.4606	−0.4253	−0.0676	0.3298	0.8108	0.4815	27
9	0.0522	−0.8498	−0.7591	−0.6414	0.4135	3.0656	0.3333	9
Low Score (1–3)	−0.1513	−1.0582	−0.6231	−0.2254	0.2655	0.6724	0.3827	81
High Score (7–9)	0.2667	−0.6476	−0.4253	0.0564	0.7694	1.5610	0.5158	95
High–Low	0.4180	0.4106	0.1978	0.2818	0.5039	0.8886	0.1331	–
t-stat/z-stat (*p*-Value)	3.2258	–	–	3.051	–	–	1.7671	–
	(0.0015)	–	–	(0.0023)	–	–	(0.0772)	–
Bootstrap Result								
1000 rep/z-stat	3.2900	–	–	3.2400	–	–	–	–
(*p*-Value)	(0.0010)	–	–	(0.0010)	–	–	–	–

Panel C: Two-Years Raw Returns

Returns	Mean	10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile	%Positive Signal	n
All Firms	1.0992	−0.5385	−0.2727	0.3846	1.6243	3.3385	0.6197	426
BrF_SCORE								
1	−0.2797	−0.3182	−0.3182	−0.2797	−0.2412	−0.2412	0.0000	2
2	0.5465	−0.7520	−0.4649	−0.1410	1.0472	2.3488	0.4333	30
3	0.3039	−0.6735	−0.3799	0.0000	0.4450	1.6874	0.4898	49
4	1.2617	−0.5214	−0.1930	0.5753	2.1306	3.7222	0.6842	76
5	0.7913	−0.5294	−0.3478	0.0639	1.0196	2.8999	0.5116	86
6	1.0328	−0.5154	−0.2237	0.4458	1.8908	2.8179	0.6591	88
7	2.3523	−0.4975	0.0353	0.8519	2.7706	6.8864	0.7797	59
8	1.1972	−0.4174	−0.0651	0.5200	1.4853	1.9118	0.7407	27

(*Continued*)

TABLE 1 Continued

Panel C: Two-Years Raw Returns

Returns	Mean	10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile	%Positive Signal	n
9	1.2901	–0.1902	0.2263	0.9789	1.6243	3.9099	0.7778	9
Low Score (1–3)	0.3794	–0.6735	–0.4000	–0.1000	0.7230	2.0006	0.4568	81
High Score (7–9)	1.9234	–0.4236	0.0320	0.7633	2.2597	3.9726	0.7684	95
High–Low	1.5440	0.2499	0.4320	0.8633	1.5367	1.9720	0.3116	–
t-stat/z-stat	3.5723	–	–	4.6570	–	–	4.2563	–
(*p*-Value)	(0.0005)	–	–	(0.0000)	–	–	(0.0000)	–
Bootstrap Result 1000 rep/z-stat	5.5900	–	–	5.1500	–	–	–	–
(*p*-Value)	(0.0000)	–	–	(0.0000)	–	–	–	–

Panel D: Two-Years Market Adjusted Returns

Returns	Mean	10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile	%Positive Signal	n
All Firms	0.4244	–1.4384	–0.7735	–0.2272	1.0405	2.4437	0.4366	426
BrF_SCORE								
1	–0.9504	–1.1193	–1.1193	–0.9504	–0.7814	–0.7814	0.0000	2
2	–0.2096	–1.9691	–1.5219	–0.3421	0.2180	2.0725	0.3667	30
3	–0.2308	–1.5317	–0.8235	–0.4906	0.1561	1.0615	0.2653	49
4	0.6724	–1.1312	–0.6543	0.0712	1.3408	2.8032	0.5132	76

5	0.0667	–1.5081	–0.8981	–0.4576	0.2906	1.9282	0.3256	86
6	0.3326	–1.4384	–0.8585	–0.1903	1.2782	2.2469	0.4432	88
7	1.6012	–1.6012	–0.5828	0.5403	2.1999	5.7781	0.6610	59
8	0.6439	–0.6099	–0.4602	–0.0202	0.7295	1.2856	0.4815	27
9	0.2571	–1.8076	–1.2157	–0.5748	1.5659	3.3697	0.4444	9
Low Score (1–3)	–0.2407	–1.6452	–0.9990	–0.4906	0.1942	1.0615	0.2963	81
High Score (7–9)	1.2018	–1.3691	–0.5748	0.3117	1.6004	3.3697	0.5895	95
High–Low	1.4425	0.2761	0.4242	0.8023	1.4062	2.3082	0.2932	–
t-stat/z-stat (*p*-Value)	3.3662	–	–	4.0030	–	–	3.8932	–
	(0.0009)	–	–	(0.0001)	–	–	(0.0001)	–
Bootstrap Result								
1000 rep/z-stat	5.1900	–	–	4.1700	–	–	–	–
(*p*-Value)	(0.0000)	–	–	(0.0000)	–	–	–	–

Note. One-Year Raw Return = buy-and-hold returns for 1-year period starting on the 1st of May of the year after portfolio formation; Two-Years Raw Return = buy-and-hold returns for 2-year period starting on the 1st of May of the year after portfolio formation; One-Year Market-Adjusted Return = buy-and-hold returns for 1-year period starting on the 1st of May of the year after portfolio formation less the value-weighted market return over the same time period; Two-Years Market-Adjusted Return = buy-and-hold returns for 2-year period starting on the 1st of May of the year after portfolio formation less the value-weighted market return over the same time period. *BrF_SCORE* ranges from 0 ("bad" signals) to 9 ("good" signals). Low *BrF_SCORE* represents firms with poor expected future performance and stock returns, while high *BrF_SCORE* is associated with firms expected to perform well. *BrF_SCORE* represents the sum of all indicator variables, or: *BrF_SCORE* = *F_ROA* + *F_CF* + *F_ΔROA* + *F_ACCRUAL* + *F_LIQUID* + *F_ ΔLEVER* + *EQ_OFFER* + *F_ΔMARGIN* + *F_ΔTURN*.

test between the difference of mean and median returns from high *BrF_SCORE* and low *BrF_SCORE* portfolios. Reported bootstrapped z-statistics (p-values) result from 1000 iterations. Table 1 panel A shows the significant difference between one-year raw returns from High Score firms and Low Score Firms. Mean returns shift from 36% to 53% considering the *BrF_SCORE* based strategy. Comparing these to low *BrF_SCORES* HBM firms' returns improve 35 p.p. and are statistically significant at 1%. The difference between median and percentage positive one-year raw returns for high and low *BrF_SCORES* firms are significant at 1% and 10% levels, respectively. Table 1 panel B documents significant differences between one-year market-adjusted returns from High Score firms and Low Score Firms. Returns shift from 5.7% to 26.7% considering a *BrF_SCORE*-based strategy. This is a considerable improvement. Comparing these to low *BrF_SCORES* HBM firms' returns improve 41.8 p.p. and are statistically significant at 1%. It is possible to differentiate the one-year market-adjusted median returns at a 1% level of significance, but the difference in percentage positive for one-year market-adjusted returns from High and Low *F_SCORE* firms are significant at 10%. Table 1, panels A and B, show that a *BrF_SCORE* strategy helps to differentiate firms with poor performance (classified in between the 10th percentile and 25th percentile) and firms with superior performance (classified above the 50th percentile) within the sample of HBM firms.

A *BrF_SCORE*-based strategy is also (and apparently even more) useful to increase subsequent two-years raw and market-adjusted returns for Brazilian firms. Table 1 panel C shows an increase of 82 p.p. if one applies the *BrF_SCORE* strategy in comparison to a HBM strategy. Table 1 panel D presents a 144% (80%), statistically significant, difference between two-years market-adjusted mean (median) returns from High and Low Score firms. Additionally there is a significant difference at the 1% level between percentage positive in two-years (raw and market-adjusted) returns from High and Low *BrF_SCORE* firms as well as for the two-years (raw and market-adjusted) median returns. Bootstrap results confirm the classical tests. The difference between two-year market-adjusted mean returns of High Score firms and all HBM firms is 78 p.p. and is statistically significant at the 1% level. These results are interesting considering the presumably lower market efficiency and poor accounting numbers in Brazil compared to the United States. Piotroski (2000) found that *F_SCORE*-based strategy improves subsequent returns, particularly over the first year. Our results suggest that financial accounting information takes a longer time to be incorporated into prices in Brazil than they do in the United States.

Size, Liquidity, and Indebtedness Effects

We classify HBM (Table 2) firms into three categories by size (small, medium, or large). The percentile size cutoffs are constructed according

TABLE 2 Buy-and-Hold Returns to a Value Investment Strategy Based on Fundamental Signals by Size Partition

Panel A: One-year market-adjusted returns for Buy-and-Hold Returns to a Value Investment Strategy based on Fundamental Signals Partitioned by Size

	Small Firms			Medium Firms			Large Firms		
Returns	Mean	Median	n	Mean	Median	n	Mean	Median	N
All Firms	0.0754	–0.1282	159	0.0542	–0.1138	140	0.0385	–0.1019	127
Low BrF_SCORE (1–3)	–0.1198	–0.2131	35	–0.3213	–0.4058	23	–0.0291	–0.1679	23
High BrF_SCORE (7–9)	0.5448	0.2278	34	0.2030	–0.1276	32	0.0110	–0.0676	29
High–Low	0.6646	2.5810	–	0.5243	2.1670	–	0.0401	0.3960	–
t-stat/z-stat (*p*-Value)	2.8300	0.0099	–	2.3279	0.0302	–	0.2150	0.6920	–
	(0.0061)	(0.0105)	–	(0.0238)	(0.0070)	–	(0.8306)	(0.7935)	–
High–All	0.4694	0.3560	–	0.1488	–0.0139	–	–0.0275	0.0343	–
t-stat/z-stat (*p*-Value)	2.5650	2.3150	–	0.8936	0.8050	–	–0.1964	0.0800	–
	(0.0111)	(0.0206)	–	(0.3728)	(0.4210)	–	(0.8446)	(0.9365)	–

Panel B: One-year market-adjusted returns for Buy-and-Hold Returns to a Value Investment Strategy based on Fundamental Signals Partitioned by Stock Liquidity Ratio

	Low Liquidity			Medium Liquidity			High Liquidity		
Returns	Mean	Median	n	Mean	Median	n	Mean	Median	n
All Firms	0.2222	0.0045	142	–0.0040	–0.1131	142	–0.0460	–0.1658	142
Low BrF_SCORE (1–3)	–0.0056	–0.2193	22	–0.3270	–0.4329	27	–0.1031	–0.1020	32
High BrF_SCORE (7–9)	0.5831	0.3988	40	0.1923	0.1651	23	–0.0753	–0.1816	32
High–Low	0.5887	0.6180	–	0.5193	0.5980	–	0.0278	–0.0796	–
t-stat/z-stat (*p*-Value)	2.2964	2.5600	–	2.6594	2.6960	–	0.1390	0.2620	–
	(0.0252)	(0.0105)	–	(0.0106)	(0.0070)	–	(0.8899)	(0.7935)	–
High–All	0.3609	0.3943	–	0.1962	0.2782	–	–0.0293	–0.0158	–

(*Continued*)

TABLE 2 Continued

	Low Liquidity			Medium Liquidity			High Liquidity		
Returns	Mean	Median	n	Mean	Median	n	Mean	Median	n
t-stat/z-stat (*p*-Value)	2.1336	2.2020	–	1.0790	1.6160	–	–0.1999	–0.5170	–
	(0.0342)	(0.0277)	–	(0.2822)	(0.1061)	–	(0.8418)	(0.6054)	–

Panel C: One-year market-adjusted returns for Buy-and-Hold Returns to a Value Investment Strategy based on Fundamental Signals Partitioned by Indebtedness

	Low Debt			Medium Debt			High Debt		
Returns	Mean	Median	n	Mean	Median	n	Mean	Median	n
All Firms	0.0031	–0.1353	142	0.1357	–0.0555	143	0.0328	–0.1282	141
Low BrF_SCORE (1–3)	–0.1147	–0.3095	22	–0.0352	–0.2964	31	–0.3085	–0.2171	28
High BrF_SCORE (7–9)	0.0666	–0.1561	32	0.3985	0.1814	32	0.3372	0.1730	31
High–Low	0.1813	0.1534	–	0.4337	0.4778	–	0.6458	0.3901	–
t-stat/z-stat (*p*-Value)	0.6986	0.5810	–	2.0118	1.8560	–	3.1922	2.9140	–
	(0.4879)	(0.5613)	–	(0.0487)	(0.0635)	–	(0.0023)	(0.0036)	–
High–All	0.0635	–0.0208	–	0.2628	0.2369	–	0.3045	0.3012	–
t-stat/z-stat (*p*-Value)	0.3945	0.0140	–	1.5271	1.4550	–	1.7969	1.9840	–
	(0.6937)	(0.9892)	–	(0.1286)	(0.1456)	–	(0.0741)	(0.0473)	–

Note. One-Year Market-Adjusted Return = buy-and-hold returns for 1-year period starting on the 1st of May of the year after portfolio formation less the value-weighted market return over the same time period. We classify firms as small, medium, or large based on their prior year's distribution of firm market value (*MVE*). The 33.3 and 66.7 percentiles represent the cutoffs. We classify firms' stock as low liquidity, medium liquidity, or high liquidity based on their prior year's distribution of liquidity ratio. This ratio considers both, numbers of shares traded and volume traded during the year of portfolio implementation. The 33.3 and 66.7 percentiles represent the cutoffs. We classify firms' indebtedness as low debt, medium debt, or high debt based on their prior year's distribution of debt to debt plus equity ratio. The 33.3 and 66.7 percentiles represent the cutoffs. *BrF_SCORE* ranges from 0 ("bad" signals) to 9 ("good" signals). Low *BrF_SCORE* represents firms with poor expected future performance and stock returns, while high *BrF_SCORE* is associated with firms expected to perform well. *BrF_SCORE* represents the sum of all indicator variables, or: *BrF_SCORE = F_ROA + F_CF + F_ΔROA + F_ACCRUAL + F_LIQUID + F_ ΔLEVER + EQ_OFFER + F_ΔMARGIN + F_ΔTURN*.

to the firms' 33.3 and 66.7 percentiles distributions of the previous year's *MVE*. The HBM sample for Brazilian firms is composed mostly of small companies. We present buy-and-hold market-adjusted returns for one year and two years after the portfolio construction. The results presented in Table 2 panel A indicate the excess returns earned by the High *BrF_SCORE* strategy can statistically differentiate between winners and losers only for small and median firms considering the one-year market-adjusted mean and median returns earned from a strategy long on High Score firms and Short on Low Score firms. The strategy based on High *BrF_SCORE* small firms also differentiates one-year market-adjusted mean and median returns from the returns obtained by a strategy based on all HBM small firms. Comparing our results to Piotroski's (2000),[10] one realizes that the amount of return that financial statement analysis can provide in an environment like Brazil seems much higher than in the United States, and our strategy differentiates essentially between HBM small and medium firms. Another important feature is to analyze how the *BrF_SCORE* strategy works regarding the liquidity of firms' shares. The Spearman correlation between classification of firm size and liquidity is 0.46, so we implement an additional analysis for stock's liquidity partition. We classify firms' stock as low liquidity, medium liquidity, or high liquidity based on their year distribution of liquidity ratio. This ratio considers both numbers of shares traded and volume traded during the year of portfolio implementation. The 33.3 and 66.7 percentiles represent the cutoffs. The strategy works (Table 2) for low and medium liquidity stocks for one-year market-adjusted returns to separate High *BrF_SCORE* and Low *BrF_SCORE* firms a 5% significance level.

When considering the effectiveness of the strategy for one-year market-adjusted returns resulting from a long position on highly scored firms with all HBM firms, one can realize (Table 2, Panels A and B) they are significant only for the partitions of small firms and low liquidity firms. The returns of the strategy based on long-short and even exclusively in long positions on HBM firms may not hold when applied to medium and large firms or medium and highly liquid traded stocks. This fact may raise the question whether the practical implementation of the strategy is possible or whether price effects would prejudice it.

Finally we classify firms' indebtedness as low debt, medium debt, or high debt based on their prior year's distribution of debt to debt plus equity ratio. The 33.3 and 66.7 percentiles represent the cutoffs. Results from Table 2, panel C show that the investment strategy works better for firms with higher indebtedness levels. Piotroski (2000) found evidence that the accounting-based fundamental analysis strategy works for HBM firms independently of their level of financial distress. We find evidence that fundamental analysis differentiates winners from losers for firms with higher indebtedness levels. Our result can be explained by the enhanced power of fundamental analysis when it is applied to more distressed firms. In an environment like Brazil the outcome of fundamental analysis applied to HBM firms with high indebtedness levels suppresses the low quality of accounting reports. These results are consistent with abundant evidence that size affects the results of accounting-related anomalies (Foster, Olsen, & Shevlin, 1984; Mohanram, 2005; Piotroski, 2000).

Restrictions to Arbitrage and Information Environment

Beyond investigating the effect of illiquidity, size, and indebtedness on abnormal returns we directly check the effect of limits to arbitrage. The São Paulo Stock Exchange (BM&FBOVESPA)[11] provides an interesting setting to directly control for limits to arbitrage because restrictions to trade and arbitrage apply to the majority of shares. However, for a fraction of the shares traded arbitrage is possible. BM&FBOVESPA is the only stock exchange in Brazil where shares can be traded in the main market and in the access (SOMA) market. BM&FBOVESPA also lists derivatives (options and forwards) of the shares traded on its main floor. There is a future contract based on the IBOVESPA (the stock index of the shares traded at BM&FBOVESPA) traded on BMF (The Brazilian Exchange where derivatives based on commodities, indexes, and rates are traded). The IBOVESPA does not provide a substitute for the shares traded at BM&FBOVESPA because it is based on the most liquid shares (the 52 most liquid shares in January 2008) and not on a representative sample of the shares traded in São Paulo. Short selling is only allowed for a few shares—generally the more liquid ones.

We select firms for which arbitrage is possible by hand picking firms with the following features: (i) firms that are included in the stock exchange index (IBOVESPA) and (ii) firms that have options and forwards traded on their shares—to allow short selling. We studied each firm individually over the sample period to verify if the previous conditions were present in each year. We call these the ARBITRAGE firms and show in Table 3 that the interaction of *BrF_SCORE* and ARBITRAGE is negatively related to future abnormal returns, which suggests that accounting signals are only relevant for firms for which arbitrage is not possible. Table 3, panel A, model (A) considers the association between *BrF_SCORE* and ARBITRAGE and shows that the possibility of arbitrage makes the strategy practically ineffective. Table 3, panel A, model (B) show that the *BrF_SCORE* is not significantly related to future abnormal returns for firms where arbitrage is possible, whereas it remains positively associated to one-year market-adjusted returns for firms where arbitrage is not possible. Finally Table 3, panel B, shows the results of one-year market-adjusted returns for a buy-and-hold strategy based on fundamental signals partitioned by arbitrage possibility. Results show that buy-and-hold returns from high *Br_FSCORE* firms and

TABLE 3 Regressions

Panel A from this table presents the results of pooled cross sections robust regressions for one-year market-adjusted returns (*MA_RET_1*) controlling for *LIQUIDITY, MVE, BM, ACCRUAL, MOMENT, EQ_OFFER, BrF_SCORE* and *ARBITRAGE*BrF_Score* for both all samples of firms and high book-to-market firms. Additionally we split our analysis on firms where arbitrage is possible and where no arbitrage is possible due to limits on trading. Coefficients are shown on the first line, [t-statistics] appear on the second line and (p-values) on the third line. Panel B presents the buy-and-hold returns to financial statements analysis based on fundamental signals partitioned by the possibility of arbitrage. The low BrF_SCORE portfolio consists of firms with an aggregate score of 1–3 while the High BrF_SCORE represents firms with a score of 7–9.

Panel A: Pooled Cross Section Regressions

Coefficients from Pooled Regression - dependent variable: MA_RET1

	Intercept	Ln (*MVE*)	Ln (*BM*)	*MOMENT*	*ACCRUAL*	*EQ_OFFER*	*LIQUIDITY*	*BrF_ SCORE*	*ARBITRAGE* BrF_SCORE*	Adj. R2
Model (A) –all	–0.4451 [–2.49] (0.013)	0.0235 [2.14] (0.033)	0.0980 [4.44] (0.000)	0.0014 [4.25] (0.000)	0.0380 [0.51] (0.612)	–0.0598 [–0.72] (0.471)		0.0197 [2.15] (0.032)	–0.0181 [–2.25] (0.024)	0.0290
Model (A) –HBM	–1.2523 [–2.98] (0.003)	0.0524 [1.77] (0.078)	0.1947 [2.65] (0.008)	0.0009 [1.19] (0.234)	0.1663 [0.40] (0.686)	0.1818 [0.99] (0.321)		0.0430 [1.58] (0.116)	–0.0450 [–1.06] (0.289)	0.0324
Model (B) –all	–0.8301 [–4.17] (0.000)	0.0464 [3.95] (0.000)	0.1053 [4.77] (0.000)	0.0013 [3.99] (0.000)	0.0388 [0.52] (0.606)	–0.0619 [–0.76] (0.450)	–0.0253 [–4.06] (0.000)	0.0171 [1.88] (0.060)		0.0369
Model (B) –HBM	–2.4423 [–4.58] (0.000)	0.1152 [3.81] (0.000)	0.2353 [3.09] (0.002)	0.0007 [1.01] (0.312)	0.0484 [0.12] (0.904)	0.3145 [1.73] (0.084)	–0.0658 [–3.72] (0.000)	0.0280 [1.05] (0.294)		0.0708
Model (B) –all firms with possible arbitrage	–1.4464	0.0813	0.0377	0.0036	1.3915	0.0627	0.0648	–0.0083		0.2276

(*Continued*)

TABLE 3 Continued

	Intercept	Ln (*MVE*)	Ln (*BM*)	*MOMENT*	*ACCRUAL*	*EQ_OFFER*	*LIQUIDITY*	*BrF_ SCORE*	*ARBITRAGE* BrF_SCORE*	Adj. R2
	[−1.89] (0.062)	[1.72] (0.089)	[0.80] (0.426)	[2.61] (0.010)	[3.40] (0.001)	[0.48] (0.632)	1.16 (0.250)	[−0.45] (0.651)		
Model (B) –all firms with no possible arbitrage	−0.8555	0.0482	0.1082	0.0013	0.0232	−0.0631	−0.0247	0.0189		0.036
	−3.97 (0.000)	[3.73] (0.000)	[4.57] (0.000)	[3.82] (0.000)	[0.31] (0.758)	−[0.64] (0.525)	−3.84 (0.000)	[1.96] (0.050)		

Panel B: One-year market-adjusted returns for Buy-and-Hold Returns to a Value Investment Strategy based on Fundamental Signals by arbitrage possibility

Returns	Mean	10th Percentile	25th Percentile	Median	75th Percentile	90th Percentile	n
All firms with possible arbitrage	−0.0983	−0.5837	−0.3256	−0.0615	0.1501	0.3370	107
Low Score (1–3)	−0.0764	−0.5029	−0.2676	−0.0614	0.1217	0.2062	11
High Score (7–9)	−0.1343	−0.6264	−0.4807	−0.0816	0.1494	0.4136	44
High–Low	−0.0579	−0.1235	−0.2131	−0.0202	0.0277	0.2074	–
t-stat/z-stat	−0.4229	–	–	0.2950	–	–	–
(*p*-Value)	(0.6741)	–	–	(0.7683)	–	–	–

Bootstrap Result							
1000 rep/z-stat	–0.4500	–	–	0.3300	–	–	–
(*p*-Value)	(0.6510)	–	–	(0.7380)	–	–	–
All firms with no possible arbitrage	–0.0402	–0.7601	–0.4848	–0.1435	0.2731	0.7497	2044
Low Score (1–3)	–0.1250	–0.8541	–0.5417	–0.2472	0.2241	0.6724	289
High Score (7–9)	0.0157	–0.6992	–0.4194	–0.0881	0.2942	0.7694	587
High–Low	0.1407	0.1549	0.1223	0.1591	0.0701	0.0970	–
t-stat/z-stat	2.9247	–	–	3.5500	–	–	–
(*p*-Value)	(0.0035)	–	–	(0.0004)	–	–	–
Bootstrap Result							
1000 rep/z-stat	2.9700	–	–	3.8500	–	–	–
(*p*-Value)	(0.0030)	–	–	(0.0000)	–	–	–

Note. MA MA_RET1 = buy-and-hold market adjusted returns for 1-year period starting on the 1st of May of the year after portfolio formation; *Ln(MVE)* = natural logarithm of market value of equity at fiscal year-end. *Ln(BM)* = book value of equity at fiscal year-end scaled by *MVE; MOMENT* = six month buy-and-hold return prior to portfolio formation; *ACCRUAL* = changes on noncash current assets minus changes on current liabilities (except short-term debt) minus depreciation, scaled by beginning-of-the-year total assets; *LIQUIDUTY* = liquidity index is calculated as: ln(100 * p/P * sqrt(n/N * v/V)), where p is the number of days in which there were at least 1 trade of the stock during the period; P is the total number of days in the period; n represents the number of trades of the stock during the period; N represents the total number of trades of all the stocks in the period; v is the volume in monetary terms of the stock in the period and; V represents the total volume in monetary terms of all the stocks in the period; *ARBITAGE =1* for firms where arbitrage is possible; zero otherwise. We consider that arbitrage is possible for firms with the following features: (i) firms which are included in the stock exchange index (IBOVESPA) and (ii) firms which have options and forwards traded on their shares—to allow short selling; *ARBITAGE*BrF_SCORE* = interaction between firms with possible arbitrage and *BrF_SCORE*.

low *Br_FSCORE* firms are statistically different only for firms where arbitrage is not possible.

Our results confirm that excess returns to strategies based on financial statement analysis are generated mainly by firms for which arbitrage is not possible. Thus one cannot actually generate profits without incurring risk for these shares—these strategies are not actually implementable in our setting. The abnormal returns we observe are returns to idiosyncratic risk and not real excess returns. By directly controlling for limits to arbitrage we avoid the controversies surrounding proxies for restrictions to trade like idiosyncratic volatility previously used in the literature (Ali, Hwang, & Trombley, 2003; Brav, Heaton, & Li, 2010; Mashruwala et al., 2006; Mendenhall, 2004; Pontiff, 1996, 2005; Wurgler & Zhuravskaya, 2002).[12]

Our results are not significantly affected when we control for transactions costs. Using Stoll's (1991) approach we estimate transactions costs to be significant in Brazil especially for low liquidity shares but not large enough to change our results, adding to the idea that fundamental strategies analysis only work for small, low liquidity firms and especially for firms for which arbitrage is not possible. However, transaction costs are not significantly large enough to explain the excess returns that financially strong HBM firms obtain in Brazil. Our result corroborates Ball (1990) who argued that a meaningful definition of efficiency should require that frictions such as transactions costs and trading restrictions do not influence price. Our results also confirm evidence presented by Bernard (1993, p. 321) with respect to short-selling in the United States[13].

ROBUSTNESS ANALYSIS

Applying Mohanram (2005) Strategy to LBM Firms

Our evidence indicates that results of HBM investment strategy applied to Brazilian capital markets are influenced by low liquidity and, consequently, to limits to arbitrage. However, one could argue whether the same conclusions would hold for LBM firms. To address this question further we apply Mohanram's (2005) strategy for LBM firms on BM&FBovespa. In this sense we apply an adapted[13] version of Mohanram's (2005) strategy to Brazilian listed firms. When investigating the impacts of the strategy for LBM firms and arbitrage partitions, in the same way as implemented for HBM firms in our previous analysis, we do not find evidence of abnormal returns for the strategy. Actually, our conclusions are similar to the results of the HBM firm strategy, that is, it is obtained from the firms where arbitrage is not possible. Table 4, panel A presents one-year market-adjusted returns on *BrG_Score* strategy for LBM firms by arbitrage partitions. Results indicate that the long-short strategy is significant at the 1% level to differentiate returns from high

TABLE 4 Market-Adjusted Returns to an Investment Strategy Based on BrG_Score in Low Book-To-Market Firms by Partitioned by the Possibility of Arbitrage

Panel A: One-year market-adjusted returns						
	Arbitrage is possible			Arbitrage is NOT possible		
Returns	Mean	Median	n	Mean	Median	N
All Firms	–0.0893	–0.0943	91	–0.1282	–0.0659	303
BrG_SCORE						
0	na	na	0	–1.1263	–1.1263	1
1	0.7422	0.7422	2	–0.4698	–0.2471	5
2	0.2375	–0.0509	7	–0.5773	–0.0977	18
3	–0.4627	–0.3203	12	–0.3281	–0.1743	45
4	–0.1414	–0.1375	28	–0.3289	–0.1633	84
5	–0.0965	–0.0307	18	0.1346	0.1387	74
6	–0.2223	–0.2159	12	0.1301	–0.0166	57
7	0.1237	0.0645	10	–0.0575	–0.0234	14
8	0.7017	0.7017	2	0.1701	0.1213	5
Low Score (0–3)	–0.1145	–0.1461	21	–0.4149	–0.1743	69
High Score (6–8)	–0.0420	–0.0307	42	0.1162	0.0299	150
High–Low	0.0725	0.1154	–	0.5311	0.2042	–
t-stat/z-stat (*p*-Value)	0.3104	0.8750	–	2.659	2.7550	–
	(0.3787)	(0.3817)	–	(0.0042)	(0.0059)	–
High–All	0.0473	0.0635	–	0.2443	0.0959	–
t-stat/z-stat (*p*-Value)	0.3028	0.3730	–	1.7349	1.7510	–
	(0.3812)	(0.7093)	–	(0.0417)	(0.0800)	–

(*Continued*)

TABLE 4 Continued

Panel B: Two-year market-adjusted returns

	Arbitrage is possible			Arbitrage is NOT possible		
Returns	Mean	Median	n	Mean	Median	n
All Firms	–0.0734	–0.0641	91	–0.1457	–0.1190	299
BrG_SCORE						
0	na	na	0	–1.1263	–1.1263	1
1	1.0662	1.0662	2	–0.4088	–0.1390	5
2	0.2871	0.0109	7	–0.6000	–0.1260	18
3	–0.3419	–0.2319	12	–0.3258	–0.2645	44
4	–0.1468	–0.1264	28	–0.3759	–0.2000	82
5	–0.1199	–0.0869	18	0.1315	0.0480	73
6	–0.2216	–0.1632	12	0.0952	–0.1394	57
7	0.1049	0.1103	10	–0.0430	0.0118	14
8	0.5782	0.5782	2	0.2297	0.1832	5
Low Score (0–3)	0.0019	–0.1027	21	–0.4162	–0.1756	68
High Score (6–8)	–0.0622	–0.0491	42	0.1045	–0.0085	149
High–Low	–0.0641	0.0536	–	0.5207	0.1671	–
t-stat/z-stat (*p*-Value)	–0.3023	–0.4810	–	2.6186	2.5520	–
	(0.6183)	(0.6304)	–	(0.0047)	(0.0107)	–
High–All	0.0113	0.0150	–	0.2502	0.1105	–
t-stat/z-stat (*p*-Value)	0.0769	0.2280	–	1.8071	1.6400	–
	(0.4694)	(0.8200)	–	(0.0357)	(0.1011)	–

Note. *BrG_SCORE* is the sum of eight signs (G1:G8), that have a default value of 0 and equal 1 if the following criteria are met: G1: ROA ≥ industry median, G2: CFROA ≥ industry median, G3: CFROA ≥ ROA, G4: Δ%ROA ≤ industry median, G5: Δ%GSAL ≤ industry median, G6: DefAINT ≥ industry median, G7: CAPINT ≥ industry median, G8: SINT ≥ industry median. ROA is net income scaled by average assets. CFROA is cash from operations scaled by average assets. Δ%ROA and Δ%GSAL are the percentage growth of ROA and SGR respectively measured over the last year. DefAINT is deferred assets scaled by total assets. CAPINT is capital expenditure scaled by total assets. SINT is selling expenses divided by total assets. Industry medians are calculated at the level one NAICS within LBM firms.

BrG_Score firms from low *BrG_Score* only when implemented to the partition of firms where arbitrage is not possible. Additionally, results show that implementing the long strategy for the group of firms where arbitrage is possible would drive away the significant differences on returns when compared to the full sample of LBM firms. Table 4, panel B presents similar analysis and results for the two-years market-adjusted returns on *BrG_Score* strategy for LBM firms by arbitrage partitions.

In general this analysis shows that consistent with the results obtained for HBM firms, the possibility of arbitrage seems to play an important role in determining returns for FSA strategies in Brazilian Capital markets.

CONCLUSIONS

This article investigates if accounting-based fundamental analysis strategy can help investors earn excess returns on portfolios of HBM and LBM firms in a narrow equity market like Brazil, the biggest and most representative equity market in Latin America. We find evidence that a financial statement analysis strategy based on financially strong HBM firms or financially strong LBM firms apparently can separate winners from losers in an environment like Brazil. An investor could have increased his or her HBM portfolio one-year (two-year) market-adjusted returns from 5.7% (42.4%) to 26.7%% (120.2%) selecting financially strong HBM firms in the 1994–2004 period. The results of the strategy for LBM firms indicate that selecting LBM firms based on high *BrG_SCORE* would change an investor mean (median) one-year market adjusted return from –11.9% (–7.4%) to 8.1% (2.5%). Additionally a strategy based on forming portfolios long on financially strong HBM firms and short on financially weak HBM firms generates 41.8% annual (or 144.2% for two years accumulated) market-adjusted return to portfolios implemented from 1994 to 2004. Long positions on financially strong LBM firms and short positions on financially weak LBM firms generate a 42.6% annual market-adjusted return to portfolios implemented from 1994 to 2004.

Additional tests to HBM firms, however, show that small, illiquid or highly indebted firms mainly drive these results. Our specifications show that accounting-based signals are useful to predict future abnormal returns especially for small, liquid firms that do not possess derivatives based on their stocks and are not part of the stock index. These stocks do not allow arbitrage and so prices do not converge to fundamentals as quickly as they would if markets were efficient. If arbitrageurs try to exploit this FSA-based investment strategy, mispricing elimination would be unlikely due to the difficulty of practically implementing this strategy. Similar results hold for our sample of LBM firms. When analyzing the returns of FSA strategies by partition where arbitrage is and is not possible, results are not consistent. Actually, the excess returns can be identified only in the subsample where arbitrage is not possible.

Our results contribute to the literature on financial statement analysis and on emerging markets finance by showing the relative importance of restrictions to arbitrage on the prediction of future abnormal returns and on the implementation of FSA strategies. Our results, however, do not suggest that the analysis of financial statements is not a worthwhile endeavor and that students should stop learning and practitioners should stop examining financial reports. Real-world fundamental analysis involves more than the simple score we used in this study and it is possible that experienced and more skillful analysts are able to uncover information from financial statements and generate superior returns than the market average. This, however, is a question for future research that we did not address in this article. We also do not provide any behavioral explanations for the results found because we do not take any behavioral characteristic of traders into account and simply provide a different control for limits to arbitrage than previously done in the literature. Finally it is also important to note that the recent development of Brazilian equity markets and the increase on stocks liquidity (especially stocks that are not a part of the Ibovespa Index) could impact the results from tests that use more recent data. This improvement is also perceived by Chong and López-de-Silanes (2007b) in their acknowledgement that there is slow movement toward legal reforms intended to protect investors and make regional markets more attractive to investors in Latin America. Future research can explore the new environment in Brazil and in Latin America to investigate FSA efficiency and its relationship to arbitrage.

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NOTES

1. We used the BM&FBovespa (São Paulo Stock Exchange) to collect our data. BM&FBovespa possess a complete array of financial products for trading in equity and equity related derivatives as well as structured transactions and financial products for trading on OTC markets and on cash markets. According to BM&FBovespa's IPO prospectus, from 2002 to 2007 BM&FBovespa had the highest growth in America and the third in the world regarding daily traded volume.

2. Bernard (1993) provides an interesting survey of this topic.

3. Based on CRSP and Economatica data.

4. An interesting example is the smallest IPO ever at BM&FBovespa. In January 2005 a company filed for an IPO raising approximately US $6 million. The firm's stockholder equity before the new funding was approximately US $12 million, considerably smaller than the average for firms previously listed at BM&FBovespa.

5. Brazilian firms can issue common and/or preferred shares and both are considered as equity sources.

6. For all variables that should be scaled by total assets from the beginning-of-the-year of 1994 we use the assets for the end-of-the-year. This procedure is necessary due to the end of monetary correction related to inflation rates that existed until 1994 in Brazil. After that year monetary correction is not accounted for.

7. We select this range due to consistency of accounting standards. Until 1994 Brazilian financial statements were adjusted for price level changes. Additionally the Brazilian GAAP significantly changed after 2007.

8. As stated in Section 3, both preferred or common stocks are considered to be equity in Brazil. Usually the preferred stock has higher liquidity than common shares. To select the most liquidity class of shares we use the stock liquidity ratio that is calculated as the ratio of the number of days in which there were at least one trade of the stock during the year to the total number of days in the year multiplied by the square root of the ratio of number of trades of the stock during the year to the total number of trades of all stocks in the year times the ratio of volume in monetary terms of the stock in the year to total volume in monetary terms of all stocks in the same year.

9. We use IBRX as benchmark. IBRX represents a Brazilian stock market index composed by the most 100 liquid stocks traded on BM&FBovespa. We also use other proxies for excess returns like the one obtained using the market model and the one factor CAPM. Our results do not change significantly.

10. Table 4, page 21.

11. More information can be found on www.bmfbovespa.com.br.

12. One could argue that limits to arbitrage are not important for long strategies. They are, however, because investors need to sell stocks or indexes in order to protect their positions against general market fluctuations.

13. Indeed, most (not all) of the fund managers that trade on SUE-related (standardized unexpected earnings) signals and with whom I have spoken do not attempt to sell short on bad news, and trade only within a universe of the 500 or 1000 largest stocks on the NYSE, where transactions are lower, and where large positions can be taken without much concern about price pressure.

14. We use an adapted version due to restrictions on data availability necessary to the exact replication of the strategy.

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