Firm profitability and expected stock returns: Evidence from Latin America

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Abstract

Despite their higher valuation ratios, larger size, and higher investment needs, profitable firms outperform, in both raw and risk-adjusted returns, unprofitable firms in Latin America. The positive effect of firm profitability on stock returns is pervasive in univariate and bivariate sorts, panel regressions, across sub-regional markets, and among small and large stocks. A five-factor model that includes market, size, distress, profitability, and investment factors prices profitability portfolios better than other popular factor models. Five-factor alphas of profitability portfolios tend to be lower and less statistically significant, both individually and collectively, than alphas from other three widely-used pricing models.

JEL Classification: G11; G12; G15

Keywords: operating profitability; cross-sectional returns; five-factor model; Latin America

1. Introduction

Several recent papers focusing on the U.S. stock market have analyzed the impact of firm profitability on the cross-section of stock returns. Novy-Marx (2013) finds that gross profitability (i.e., gross profits over assets) has a positive and significant predicting power in the cross section of returns beyond value, size, and momentum effects. This finding is difficult to reconcile with previous evidence by Fama and French (1993) in which the HML factor absorbed time variation of relative earnings in a setting where low book-to-market (BM) firms showed high (not low) and persistent earnings while high BM firms showed the opposite. Ball, Gerakos, Linnainmaa and

Nikolaev (2015) find that operating profits (i.e. gross profits minus selling, general, and administrative (SGA) expenses, but excluding research and development expenditures) better predict future returns than gross profits. Thus, operating profitability, instead of gross profitability (as suggested by Novy-Marx (2013)), becomes a cleaner measure of economic profitability. Noise (when predicting returns) derived from the arbitrary accounting allocation of costs between costs of golds sold (COGS) and SGA appears to dilute when both COGS and SGA are combined in an operating profitability measure. In a subsequent paper, Ball et al. (2016) document that cash-based operating profitability has a positive and significant effect on monthly returns and that the cash-based profitability measure subsumes the effects of other profitability variables like operating profits or accruals on stock returns. In all, monthly returns appear more closely related to the operating cash generated by the firm than to operating profits that involve accounting accruals adjustments. More recently, Novy-Marx (2016) find, after controlling for a new factor related to profitability, in addition to the three Fama French factors (market, size, and distress), that the abnormal returns to defensive strategies (e.g. those that take long and short positions in low beta (volatility) stocks and high beta (volatility) stocks, respectively) are no longer significant. As an illustration, consider the case of the poor performance of highly volatile stocks. This underperformance derives from the fact that high volatility stocks usually come from small and growth firms with low operational profitability. After accounting for the low profitability of highly volatile stocks, their poor returns are no longer unexpected. Extending the evidence to international markets, Sun, Wei, and Xie (2014) test for a profitability effect (using gross profits over assets as a proxy of firm profitability) on stock returns using a sample of developed and developing countries. On the whole sample, they find a positive effect of profitability on returns. Nevertheless, the effect appears confined to developed markets. Only a handful of developing countries showed a significant and positive effect of profitability on stock performance.

The theoretical motivation for a positive effect of profitability on stock returns can be possibly traced to the dividend discount model of Miller and Modigliani (1961). According to that model, the market value of equity at time t (M_t) is equal to the sum of expected dividends discounted at the internal rate of return on expected dividends (r). The internal rate of return on dividends is roughly equal to the long term expected stock return. The valuation formula is then:

$$M_t = \sum_{\Delta=1}^{\infty} \frac{E(Y_{t+\Delta} - dB_{t+\Delta})}{(1+r)^{\Delta}}, \tag{1}$$

Where Y_t is equal to equity earnings at time t, and $dB_{t+\Delta}$ is equal to the change in book equity (B) from time t to t+Δ. Normalizing both sides of the equation by B_t, one can expect the following relationships. If we hold fixed M_t, B_t and $dB_{t+\Delta}$, a higher profitability (Y) translates into a higher expected stock return. Furthermore, if we hold constant Y_t, B_t, and $dB_{t+\Delta}$, a lower M_t implies a higher expected return. In addition, one can expect a negative relationship between expected investment ($dB_{t+\Delta}$) and r holding everything else constant. Fama and French (2006) find evidence in the U.S. consistent with the predictions of the dividend discount model. For example, controlling for book-to-market and investment effects, more profitable firms are likely to have higher expected returns. In addition, controlling for investment and profitability effects, firms with higher book-to-market ratios have higher expected returns.

In this paper we focus on one of the predictions of the dividend discount model. We thoroughly examine whether higher firm profitability implies a higher expected stock return in Latin America. Our analyses concentrate on whether firm profitability shows forecasting power on stock returns making use of both univariate and bivariate portfolio sorts as well as multivariate regressions. To analyze the economic or practical significance of our findings (and rule out that our findings are driven by the existence of small and often highly illiquid and difficult to trade stocks) we shed light on the profitability effect for both small and large stocks. In essence, we find that the profitability effect (using operating profits as a more comprehensive profitability proxy) in Latin America is pervasive; it is evident for the whole sample and across subsamples of small and large stocks.

Our main contributions are two-fold. First, we extend the evidence of a positive profitability effect to a growing emerging market. Our out-of-sample analysis covers the five largest national stock markets in Latin America with a combined market capitalization of 1.44. USD trillion. Fama and French (2015c) do not include the Latin American region when testing the implications of the dividend discount model, and consequently focus their analyses on four geographical regions (North America, Europe, Japan, and Asia Pacific) where market integration is a plausible hypothesis (to increase the power of their tests and the reliability of their regional pricing factors). Nevertheless, one can argue that recent market developments are moving Latin America closer to the ideal of market integration. In practice, one can distinguish two main (sub-regional) stock markets in Latin America. The BM&FBOVESPA in Brazil, and the Latin American Integrated Market or *Mercado Integrado Latinoamericano* (MILA). MILA began operating on May 30, 2011 as an integrated trading venture among the stock markets of Chile, Colombia, and Peru. The Mexican stock market later joined MILA in December 2014. By trading through MILA, for example, Mexican (or U.S.) investors are able to send market orders to buy Chilean or Colombian stocks without the need to open brokerage accounts in these two foreign markets. In all, MILA is an example of an integration effort of the four countries that now take part of the Pacific Alliance. Although integration efforts thus far have been far from perfect (e.g., cross-country trading have been scant), we think is worthwhile to study price patterns in Latin America to strengthen previous evidence of a profitability effect (and rule out data mining concerns). Second, we examine the suitability of the newly proposed five-factor model (that includes market, size and value factors as well as two new factors related to profitability and investment) to price regional profitability portfolios. By and large, Fama and French (2015a, 2015c) find that their five-factor model does a better job explaining portfolio returns than their previous three-factor model. We analyze the significance of individual alphas of profitability portfolios as well as the joint significance of the intercepts of pricing regressions using four different factor models. In line with the two cited studies, we find that the five-factor model is a superior model than others often used in the literature, given the lower magnitude of abnormal returns of profitability portfolios and the lower incidence of significant intercepts. Furthermore, the impossibility to reject the null hypothesis of intercepts (produced by the five-factor model) jointly equal to zero (Gibbons, Ross and Shanken (1989)) gives further strength to our claim of the superiority of the five-factor model.

The remainder of the paper is organized as follows. The next section describes the data of Latin American stocks. Section 3 analyzes univariate and bivariate sorts on profitability while Section 4 examines regression results on the extent and significance of a profitability effect for the entire sample and segments of the market. Section 5 studies the pricing power of the recent five-factor model of Fama and French (2015a) when applied to profitability portfolios in the region. Finally, Section 6 concludes.

2. Data

Our sample includes both listed and delisted common stocks domiciled in Brazil, Chile, Colombia, Mexico, and Peru. These five countries are the same countries represented in the MSCI

Emerging Markets Latin America Index. More specifically, our sample includes domestic common stocks that trade on any of the five largest stock markets in Latin America (BM&FBOVESPA, Bolsa de Comercio de Santiago, Bolsa de Valores de Colombia, Bolsa de Valores de Lima and Bolsa Mexicana de Valores). From Bloomberg we extract information of end-of-month prices in U.S. dollars (USD), the book-to-market ratio of common equity, the number of outstanding shares, and accounting figures in USD (these are updated quarterly in Bloomberg). Our sample period extends from July 2001 to June 2016. The start of our sample period coincides with the month of the merger of the three local exchanges in Colombia into one national stock market.

We use three main criteria to include a stock in our sample. First, we only consider stocks with primary ticker status. This criterion helps insure that we end up with domestic stocks from the region. Second, we require a stock to show at least 42 days (roughly two months) with information (continuous or discontinuous) of the number of traded shares. Third, we include non-financial firms (as in Fama and French (1992)) that report industry affiliation (i.e., we exclude a few firms with missing industry classification benchmark information). In the end, our sample includes 582 securities from Brazil (207), Chile (136), Colombia (30), Mexico (101), and Peru (108).

The interest rate for U.S. Treasuries with one-month maturity serves as our proxy for the risk-free rate (Rf). The value-weighted (by market capitalization or the product of the number of shares outstanding times the price of a common share in month t-1) return of a portfolio, including all available stocks in a given month proxies for the market return (Rm). Since size and value factors are not available for Latin America, we proceed to construct the risk factors closely following the approach of Fama and French (1992). Each June of year t, we assign Latin American stocks into two different value-weighted portfolios: a small (S) portfolio containing stocks with below median market capitalization at the month of sorting, and a big (B) portfolio including the remaining large stocks. We also divide stocks into three value-weighted portfolios according to their book-to-market value of equity at the end of the previous fiscal year (i.e., December). The first portfolio (or growth (G) portfolio) includes stocks at the lowest 30% of the book-to-market value of equity distribution, the next portfolio (neutral (N) portfolio) is made up of stocks in the middle of the distribution (from the 30% to the 70% percentile), and the last portfolio (value (V) portfolio) comprises the remaining stocks. For the two different sorts on size and value we only consider stocks with available information of market cap for both June of year t and December of year t-1, as well as positive book-value of equity for December of year t-1.

Based on our sorting procedure we then form six size and book-to-market value of equity portfolios (SG, SN, SV, BG, BN, and BV) coming from the (independent) intersections of the two size and three book-to-market portfolios. We then tabulate for each of the six portfolios their value-weighted monthly returns for the next year (ended in June). We repeat this portfolio formation and evaluation procedure in the following year and until the end of the sample to obtain six stacked time-series of monthly portfolio returns.

A size factor (smb, "small minus big") is estimated as the average return of three long-short portfolios:

$$SMB = (SV - BV + SN - BN + SG - BG)/3, \qquad (2)$$

A distress factor (hml, "high minus low") is the mean return of two long-short portfolios related to the book-to-market value of equity of their constituent stocks1:

$$HML = (SV - SG + BV - BG)/2, \qquad (3)$$

Throughout most of the paper we use two proxies for firm profitability. First, we use the ratio of operating profits (without subtracting research and development (R&D) expenses) minus

[1] Descriptive statistics for the market, size, and distress factors as well as correlations among the factors are not reported to conserve space.

interest expense over the book value of common equity (PR/BV) as in Fama and French (2015a). Second, and for robustness purposes, we also employ the ratio of operating profits (without subtracting R&D allowances) minus interest expenses to the value of book assets (PR/AST) as a proxy for profitability as suggested by Ball et al. (2015). We lag both ratios for six months so the ratios could be available for investors at the time of portfolio formation.

Table 1 shows the annual medians of our variables. Each month we winsorize all variables at the 1 and 99 percentiles to mitigate the impact of outliers. In our calculations, we first estimate the variable in a month and then obtain the median value (in a given year). We use the median value (instead of the mean value) to reduce the influence of outliers in our estimates. We observe that 2008 (coinciding with the world financial crisis) is the year with the lowest median monthly return in excess of the risk-free rate (RET). The following year witnessed the highest median excess return. The ratio of operating profits over assets fluctuates around 1% to 2%, while the ratio of operating profits over common equity ranges from 2.3% to 4%. Focusing our attention on the last five years of the sample we observe several trends. Firm profitability tends to decrease as well as the median size or market capitalization (CAP) of the typical stock. In line with the loss of market value, the book-to-market ratio of common equity (BM) tends to increase (especially in the last two years). Finally, momentum returns (MOM) or cumulative returns from month t-2 to month t-6 are mostly negative in the last four years in line with the unwinding of the commodities boom during that time span.

Insert Table 1 here

3. Sorts on profitability

3.1. Univariate sorts

In this section we study the ability of firm profitability to predict future returns. To this end we examine the raw and risk-adjusted performance of portfolios sorted on operating profitability. We use both PR/BV and, for robustness, PR/AST, as proxies of firm profitability. Each June of year t we classify the available stocks into four portfolios from P1 (low) to P4 (high) profitability as of the end of the previous fiscal year (i.e., December of year t-1). We use quartiles given the lower availability of stocks in Latin America with respect to developed markets. Nonetheless, our results remain qualitatively similar whether we use quintile portfolios. We report our findings using value-weighted portfolios in which we allocate weights to each stock in proportion to its CAP in month t-1. We thus focus our attention on value-weighted portfolios given the findings of Hou, Xue, and Zhang (2015) that show that many of the documented “anomalies” are likely to be overstated by excessively weighting microcaps when using equally-weighted portfolios. Furthermore, simulations in Asparouhova et al. (2013) show that equal-weighting stocks in a portfolio leads to an upwardly bias in mean or risk-adjusted returns as well as in premia to stock characteristics (like size, book-to-market, and illiquidity) estimated using Fama MacBeth (1973) regressions in the presence of microstructure frictions such as non-synchronous trading, bid-ask spreads, and other sources of price deviations from underlying value. The bias is significantly reduced when one uses $t-1$ value-weighting.

We track the monthly performance of each of the four portfolios until June of year t+1. The sorting procedure is repeated and holding period returns are tabulated for the coming year. This process is repeated until the end of the sample allowing us to construct four series of value-weighted portfolio returns. We first analyze average returns of the four profitability portfolios. Then, we use each of the time series of monthly returns of the four profitability portfolios in excess of the risk-free rate as the dependent variable to estimate the Fama-French three-factor model (omitting time subscripts):

$$R_p - Rf = \alpha_p + b_p(Rm - Rf) + s_p RSMB + h_p RHML + e, \tag{4}$$

We focus on the alphas (α) or risk-adjusted returns of profitability portfolios. For inference, we use Newey-West (1987) standard errors. In panel A of Table 2 we observe average returns for the four profitability portfolios (PR/BV). Mean returns monotonically increase in profitability, and average returns for portfolios 2 to 4 are positive and statistically significant. P4, comprising the most profitable stocks, obtains very high returns close to 2% per month. Hedge portfolio returns (long on P4 and short on P1) are positive and significant reaching 1% per month consistent with the idea of a positive profitability effect in our sample. In the next panel of Table 2 we observe risk-adjusted performance that monotonically increases in profitability. Only the low (P1) and high (P4) profitability portfolios show statistically significant alphas (negative and positive respectively). The alpha of a zero- investment cost portfolio (P4-P1) allows us to determine whether profitability commands higher risk-adjusted returns. The last column of panel B shows that indeed higher firm profitability is associated with higher risk adjusted returns since the alpha of a long-short profitability portfolio is positive and significant (at a 1% significance level).

Panels C and D show similar patterns when one uses PR/AST as a sorting variable. In consequence, from here onwards, we focus our sorting analyses employing PR/BV as our profitability proxy.

We perform three robustness checks (not reported to conserve space) related to our findings of Table 2. First, we expand the pricing model (equation 4) to include a momentum factor (Carhart, 1997). The construction of a momentum factor closely resembles the construction of a value factor. We replace BM with MOM in the second sort. Furthermore, we rebalance the size and momentum portfolios each month instead of each year. The momentum factor is just the average of two high-minus-low MOM portfolios comprising small and large stocks (similar to equation 3). In short, four-factor alphas to both long and long-short profitability portfolios show similar patterns to those described in Table 2. Nevertheless, the four-factor alpha is slightly higher (lower) than the three-factor alpha for P1 (P4-P1).

Fama and French (2008) show that although microcaps account for close to 60% of the total number of stocks, microcaps make up for just 3% of total market cap. To reduce the influence of small stocks in our findings, we exclude in each month stocks in the lowest quintile of market capitalization. In all, average returns and alphas to profitability portfolios remain almost identical to those reported in this section.[2] Finally, for completeness, we employ equally-weighted portfolios to assess portfolio performance. By and large we observe a profitability premium in both average returns and alphas. Nevertheless, (negative) risk-adjusted returns are no longer significant for the low profitability portfolio and the risk-adjusted spread for P4-P1 is positive and significant although of a lower magnitude (0.7%).

Insert Table 2 here

To get a more thorough understanding of the characteristics of the constituent stocks of our four profitability portfolios, we record, each month, the median value of profitability of the stocks that belong to a given portfolio. We then average the time series of median values to obtain an estimate of the magnitude of profitability of the typical stocks in the four portfolios. We conduct a similar process for characteristics such as excess returns, market capitalization, book-to-market value of equity ratio, momentum, and asset growth. Asset growth equals the annual growth rate of book

[2] In an additional robustness check we also use a more stringent criterion for portfolio inclusion. We only consider stocks that surpass the median capitalization in the month. Using three instead of four profitability portfolios, we document positive and significant raw and risk-adjusted spreads for the long-short profitability portfolio.

assets (lagged by six months). Furthermore, we record the average number of stocks in each portfolio as well as the average fraction that each portfolio contributes to the total market cap of the sample. Table 3 reports our findings.

The typical stock in P1 has excess monthly returns close to zero while a counterpart in P4 performs much better. A similar conclusion can be reached focusing on short-term momentum (MOM). Both measures of firm profitability monotonically increase from P1 to P4. Firms in P1 show negative profitability while firms in P4 show robust operating profits (close to 10% of equity book-value). Market cap also monotonically increases in profitability. For illustration, the typical firm in P4 has a market value close to 1 billion USD. Similar to evidence reported by Novy-Marx (2013) for the U.S., high profitability firms in Latin America tend to be (large) growth stocks while low profitability firms tend to be (small) value stocks, as suggested by the negative association between profitability and BM in Table 3. In addition, more profitable firms tend to grow each year their assets more than the least profitable firms (by a ratio of almost three). Despite the fact that higher investments should translate into poorer stock returns according to the dividend discount model, profitable firms are able to outperform unprofitable firms in Latin America. On the whole, each profitability portfolio includes 56 stocks. Although, on average, each portfolio has roughly the same number of constituent stocks, P1 contributes with only 10% of the total market capitalization in a month (reinforcing the idea that P1 concentrates the bulk of small firms) while P4 contributes with 40% of the total market cap in a representative month.

Insert Table 3 here

3.2.Sorts on profitability and stock characteristics

We examine independent bivariate sorts to check whether the positive effect of firm profitability on stock performance still exists after controlling for stock characteristics that have been shown to impact returns. Our focus lies on three stock characteristics often discussed in the literature: size, book-to-market and momentum. To control for size in each month, we create two size portfolios: P1 and P2 with stocks with below and above median market cap, respectively. Furthermore, we make another sort based on profitability and create two additional portfolios (consisting of stocks with below and above median operating profitability values). In all, we end up with four portfolios created from the intersection of the 2x2 size and profitability portfolios. Each June we repeat the sorts, and track the monthly performance of the four value-weighted portfolios from July onwards. To determine whether there is a profitability effect after controlling for size, we analyze the alphas of the profitability portfolios and the alpha of a high-minus-low profitability portfolio for each of the two size subgroups. We conduct a similar bivariate analysis for characteristics such as book-to-market and momentum.

In the upper panel of Table 4 we notice a consistent profitability effect on both the small and large stock portfolios. The two high profitability portfolios deliver positive and significant alphas, although risk-adjusted returns are stronger for small and high profitability stocks. The risk-adjusted spread of the two high-minus-low profitability portfolios is positive and statistically significant. The raw spreads (not shown for brevity) of the two long-short profitability portfolios are also positive and highly significant. Across profitability portfolios (in columns) we see a negative size effect although statistically insignificant.

Moving on to double-sorted portfolios on BM and profitability, we see in the middle panel of Table 4, a positive profitability effect only for the low BM portfolios. The P2-P1 positive and significant alpha spread is driven by both the positive alpha of the high profitability portfolio and the negative alpha of the low profitability portfolio. For high BM portfolios there is a positive although insignificant profitability effect. In unreported results we observe similar patterns in average returns spreads of the two high-minus-low profitability after controlling for BM. Interestingly, one can also notice a similar pattern in average returns to that reported by Novy-Marx (2013) in the U.S. in which trading the corners of the table (i.e., long on value and highly profitable stocks and short on growth and unprofitable stocks) delivers high and positive mean returns (of 0.8% per month with a p-value of 0.094). In all, profitable value stocks outperform unprofitable glamor stocks in Latin America as well.

The lower panel of Table 4 focuses on double sorts on profitability and short-term momentum. As before, alphas increase as we move from low to high profitability. Highly profitable firms outperform (on a statistical basis) unprofitable firms only in the high momentum portfolio. We are not able to discern a profitability effect in the low-return continuation portfolio. When we pay attention to the corners of the table a profitable trading strategy emerges. By going long on high momentum and profitable stocks, and short on low momentum and unprofitable stocks one can obtain three-factor alphas close to 0.6% per month (p-value of 0.063). A positive average returns spread also holds for the same double-sorted strategy. By and large, the positive effect of firm profitability on stock performance appears to be robust after controlling for stock characteristics on an individual basis. In the following section we examine whether controlling for several stock characteristics simultaneously affects our finding of a positive ability of firm operating profitability on stock returns.

Insert Table 4 here

4. Fama and MacBeth regressions

4.1.Whole sample

Table 5 shows Fama and MacBeth (1973) regressions of monthly excess returns on profitability. We lag profitability by a quarter (instead of the commonly used one-semester lag) given the fact that Bloomberg updates accounting data with a three-month delay. Following previous studies (Novy-Marx (2013) and Ball et al. (2015) and (2016)), our regressions include control variables such as the log of size and the log of the book-to-market ratio of equity. Both variables are lagged by six months to avoid taking unintentional positions on momentum. We also control for past returns (i.e., excess returns in the prior month) to control for reversal effects analyzed in Jegadeesh (1990), as well as for short-term momentum (MOM) following Jegadeesh and Titman (1993). Given the shorter length of our panel (and to minimize information loss) we decided to control for short-term momentum using cumulative returns from months t-2 to t-6 instead of using a longer window (i.e., from month t-2 to month t-12). Importantly, our choice is influenced by the fact that short-term momentum effects (see below) manifest stronger in our sample than longer term momentum effects. In our first specification we test the univariate power of profitability (proxied by operating profits scaled by the book value of equity) to predict monthly returns. In our second specification our bivariate regression includes both profitability and size. In the next regression we examine whether both profitability and BM have predictive ability to forecast returns. In our fourth (and most complete) specification we include profitability and controls for size, BM, past returns and momentum. The remaining four specifications mirror our first four specifications except that we proxy (for robustness purposes) profitability with the ratio of operating profits scaled by the book value of assets. According to models 1 and 5 profitability has univariate and positive power to forecast excess returns. The coefficient related to profitability over assets is of a higher magnitude than the one we obtain when we scale by the book value of equity. Focusing on specifications 2 and 3 (or 6 and 7) we observe a negative size effect and a positive BM effect (controlling for profitability). The coefficient of profitability remains positive and highly significant. In our most complete specification (either specification 4 or 8) we still find a negative size effect and a positive value effect. Nonetheless, the coefficients related to size and BM are not statistically significant. It appears that both size and BM effects are subsumed by our proxy of return continuation. The coefficient of MOM is positive and highly significant. Importantly, our finding of a positive profitability effect remains intact after a including a relevant list of controls. In all, both a profitability and a momentum effect appear positive and highly significant in a multivariate setting. In addition, across our eight specifications no single intercept attains statistical significance suggesting adequate model specifications. Adjusted R^2s increase as we move to more complete specifications (e.g., from 3 to 4 or 7 to 8). The average number of firms in our monthly regressions oscillates around 200.

In unreported tests we change several assumptions of our base regressions shown in Table 5. We seek to determine whether our main finding of a positive profitability effect withstands methodological changes. Initially we change the lag of our two profitability proxies. Here we use a six month lag as is common in U.S. studies. In short, we find qualitatively similar results. In specifications 4 and 8 we still observe a positive and significant profitability (and momentum) effect. Nevertheless the univariate power of profitability to predict returns dwindles, and the coefficients attached to our two profitability proxies decrease in magnitude.

In the Miller and Modigliani model firm investment outlays negatively predict stock returns. Firms with higher investment needs are likely to underperform firms with lower investment requirements.[3] We proxy, as Fama and French (2015a and 2016), investment needs by the annual percentage change in assets (lagged by six months). We then include annual asset growth in all of

[3] In related literature, Gray and Johnson (2011) show evidence of an asset growth effect in Australia whereby high growth stocks under-perform low-growth stocks. This negative effect of asset growth on performance appears concentrated on large stocks (is non-existent for small stocks and microcaps), and persists after controlling for other characteristics that have been shown to influence returns (i.e., size, book-to-market, and past returns).

our specifications. We find negative coefficients associated to investment requirements although most of the coefficients are statistically nil (except for specification 5 where the coefficient is significant at a 10% significance level). The remaining coefficients tend to resemble those of Table 5. We also check whether differences in accounting rules across countries might alter our findings. To this end we include country dummies in our specifications. None of the country dummies turned out significant. In all, including country dummies does not change our conclusions. In a final check of our base results, perhaps differences in profitability might be related to persistent differences across industries (we have nine industries represented in our sample) that may drive our finding of a positive profitability effect. To control for industry effect we expand our specifications with industry dummies. Some of the industry dummies are significant; nonetheless, our main findings remain intact.

Insert Table 5 here

4.2. The effect of firm size on Fama and MacBeth regressions

Given the likely disproportionate effect of microcaps and small stocks in pricing regressions, Fama and French (2008 and 2016) highlight the importance of examining the extent of an anomaly across different size groups. To mitigate the influence of small and often highly illiquid stocks, we delete in Table 6 from our monthly regressions those stocks at the bottom quintile of the (monthly) market cap distribution. Similar to our findings in Table 5, we observe a positive and robust profitability effect. We witness the same patterns as before: non-significant intercepts, increasing R^2s, and positive and negative value and size effects respectively in bivariate regressions as well as positive return continuation. One notable difference here is the negative and significant size effect in specifications 4 and 8.

In a further (untabulated) attempt to dilute the influence of small firms on our Fama and MacBeth regressions we use weighted least squares (were weights are proportional to market cap in month t-1) instead of ordinary least squares (that implicitly equally weights small and large firms) in our monthly cross-sectional regressions. We average coefficients across months as before and use Newey West (1987) standard errors for inference. Our findings with respect to profitability do not change. Nevertheless we would like highlight two patterns (with respect to our findings of Table 5). A momentum effect turns out insignificant. Possibly momentum is driven by some profitable small stocks that might end up relatively over weighted by using uniform portfolio allocations. Furthermore, average R^2s increase. In specifications 4 and 8, for example, adjusted R^2s almost double. In an additional unreported check we split, each month, the sample into stocks with below ("small") and above median ("large") market cap. In the small cap segment we notice both a significant and positive profitability effect. Nonetheless the strength of the effect is stronger (i.e. higher coefficients) with respect to that reported in our base estimations of Table 5. When we turn to the large cap segment the profitability effect weakens (it is now significant only at a 10% level in specifications 4 and 8). Nevertheless, when we use weighted least squares in the large cap segment the profitability effect regains significand and remains the sole significant determinant of monthly excess returns. As an aside, we also observe negative and significant return reversal (i.e., a negative loading on t-1 returns) and size effects. We do not find evidence of momentum in large caps.

Insert Table 6 here

4.3.Profitability effect on the two main Latin American stock markets

In practice one can distinguish two main (sub-regional) stock markets in Latin America. The BM&FBOVESPA in Brazil, and the Latin American Integrated Market or *Mercado Integrado*

Latinoamericano (MILA). MILA began operating on May 30, 2011 as an integrated trading venture among the stock markets of Chile, Colombia, and Peru. The Mexican stock market later joined MILA in December 2014. By trading through MILA, for example, Mexican (or U.S.) investors are able to send market orders to buy Chilean or Colombian stocks without the need to open brokerage accounts in these two foreign markets. In all, MILA is an example of an integration effort of the four countries that now take part of the Pacific Alliance. The Alliance objective is to promote trade and investment throughout Latin American countries with geographical and commercial ties to the Pacific Ocean.

According to the World Federation of Exchanges (WFE), as of June 2016, MILA is the largest market by market capitalization ($774 USD billion) and by the number of listed firms (642 domestic companies) in Latin America. Nevertheless, even though both market capitalization ($664 USD billions) and number of listed firms (342 local firms) are lower in the Brazilian market, the value of share trading is far higher in Sao Paulo ($237 USD billion in the first half of 2016 compared to just $79 USD billion in the integrated market). In Table 7 we revisit the analyses of Table 5 to take into account the existence of two main trading blocs. We thus separately examine our findings for Brazilian and MILA firms. The upper panel of Table 7 shows regression results for domestic firms listed in Sao Paulo. For Brazilian firms, we observe both a positive and significant profitability effect. The magnitude of the profitability coefficients (in specifications 4 and 8) is slightly lower than the magnitude reported for the whole sample. The Brazilian market exhibits price patterns that resemble those studied in the U.S. Focusing on specifications 4 and 8, we notice a negative size effect as well as a short term reversal effect. MOM is positive and highly significant. Nonetheless, we are unable to evidence a value effect on Brazil. Brazilian firms represent roughly 37% of the total firms in our sample (see the last row of the table for the average number of firms in each month), very much in line with the (relative) number of listed firms according to WFE statistics.

The lower panel of Table 7 reports our findings for MILA stocks. For stock markets that take part in the MILA the profitability effect although positive and significant is weaker than the one evidence in Brazil (in specifications 4 and 8). We also notice positive return continuation both in prior month and momentum returns. Adjusted R^2s tend to mirror those depicted in Table 5.

To conclude, the positive and significant profitability effect does not seem to be driven by a single regional market nor is confined to a particular stock market. Our findings suggest that the predictive power of firm profitability on stock performance is a broad phenomenon in Latin American stock markets.

Insert Table 7 here

5. A five-factor model for Latin American stocks

Fama and French (2015a) show that a five-factor model (based on the Fama and French (1993) three- factor model and augmented by a profitability factor and an investment factor) explains, better than the three factor model, returns of portfolios of stocks sorted by size, book-to-market, profitability and investment outlays in the U.S. Fama and French (2015c) extend the evidence of the suitability of their five factor model to a sample of stocks from 23 countries which belong to four geographical regions (North America, Europe, Japan, and Asia Pacific). Initially they find that a five-factor model does a poor job explaining regional portfolios (factor) returns using global factors. They focus next on regional tests and find, by and large, evidence consistent with profitability (e.g., controlling for size more profitable firms earn higher returns than less profitable) and investment effects (e.g., controlling for book-to-market, firms with high investment requirements are poor stock performers). Furthermore, their five-factor model often outperforms (i.e., it shows lower average intercepts and higher R^2) either a three-factor or a four factor model (dropping the investment factor) when explaining returns of portfolios constructed from partitions (e.g., 25 size-B/M portfolios) of the predicting variables (size, B/M, operating profits, and investment).

Based upon these previous studies and the ample evidence shown in the previous sections of a profitability effect in Latin America either when we focus on the whole sample, across sub-regional markets, in the segment of small or large stocks as well, or when we equally- or value-weight stocks, we now study whether a five-factor model adequately prices our four long profitability portfolios as well as combinations of long-short profitability portfolios that try to capture the direct influence of firm profitability on stock returns. In all if our long or long-short portfolios show non-significant five-factor alphas, abnormal returns depicted in Table 3 are just a mere compensation for bearing higher systematic risk. We begin by constructing a profitability and an investment factor. A profitability factor (RMW or robust-minus-weak profitability) is the simple average of the difference of value-weighted portfolios of profitable minus unprofitable firms of both small and large firms. The construction of the profitability factor resembles the construction of a distress factor (see equation 3) except for the fact that we use PROFITS/BV in the second sort. As expected, the average monthly return of RMW was positive and significant. To obtain an investment factor (CMA or conservative-minus-aggressive investment) we proceed similarly except that in the second sort we use the annual growth in assets (lagged by six months). Unexpectedly, CMA average returns were slightly negative. Our pricing equation consequently becomes (omitting time subscripts):

$$R_p - Rf = \alpha_p + b_p(Rm - Rf) + s_p RSMB + h_p RHML + r_p RRMW + c_p RCMA + e, \quad (5)$$

Table 8 shows alphas and portfolio sensitivities (*b*, *s*, *h*, *r*, and *c*) to five systematic risk factors as well as adjusted R^2 from time series regressions of our four (long) profitability portfolios as for six combinations of long-short profitability portfolios. Focusing on our four (long) profitability portfolios we see non-significant five-factor alphas. For example, the negative alpha of P1 is of a lower (absolute) magnitude to that reported in Table 3 (-0.7% per month). The lower (absolute) alpha of P1 in Table 8 can be rationalized by the negative and highly significant loading of P1 on the profitability (RMW) factor. Portfolio betas are close to one. The loadings on SMB and HML suggest (as we saw in Table 3) that P1 and P2 tend to consist of mostly small and value stocks while P3 and P4 comprise large and growth stocks. In terms of sensitivities to RMW, stocks in P1 and P2 are evidently unprofitable stocks while stocks in P3, and especially in P4 are profitable stocks. None of the CMA sensitivities is statistically significant suggesting a lack of explanatory power of an investment factor. Looking at the bottom of the table our long-short profitability portfolios are completely priced by the five-factor model. P4-P1 shows negative loadings on SMB and HML suggesting that the spread is driven by large and growth stocks. Importantly, P4-P1 shows a positive and highly significant loading with respect to a profitability factor. For five out six of our long-short portfolios we observe a positive and significant loading on a robust-minus-weak profitability factor. Adjusted R^2s are smaller for the long-short portfolios than for the long-only portfolios.

In an unreported robustness check we examine the pricing ability of the five-factor model to price equally-weighted profitability portfolios. Results remain qualitatively the same as we observe non-significant alphas and highly significant RMW loadings for most of the portfolios. Furthermore, high profitability portfolios share characteristics of large and growth stocks while low profitability portfolios behave like small and value stocks.

Insert Table 8 here

The GRS statistic of Gibbons, Ross, and Shanken (1989) is frequently used to assess the suitability of a pricing model. If intercepts in regressions of excess returns on factor portfolio returns (or right-hand side, RHS, portfolios) are jointly indistinguishable from zero one then concludes that the factor model adequately prices the left-hand side (LHS) portfolios. Gibbons, Ross, and Shanken (1989) show (as well as Fama and French 2015b) that when one cannot reject the null hypothesis of zero intercepts one can interpret this findings as if one could not increase the Sharpe ratio of the tangency portfolio by adding the LHS portfolios to the opportunity set (that initially includes the RHS portfolios). In all, the tangency portfolio constructed from RHS portfolios coincides with ("spans") the tangency portfolio constructed from both LHS and RHS portfolios (when the null hypothesis of the GRS test is not rejected).

In particular, we examine the pricing ability of four pricing model to price our four LHS profitability portfolios. We thus examine a one-factor (CAPM), three-factor (Fama and French (1993), four-factor (Carhart, 1997) and five-factor (Fama and French, 2015a) model. Table 9 reports the values of both the GRS statistic and the corresponding probability value (p-value) for the four models. It is straightforward to see that as we move from a one-factor to a five factor model the value of the GRS statistic decreases (and correspondingly, the p-values decrease). Importantly, one can reject the null of jointly-equal to zero intercepts for the CAPM, the three-factor, and the four-factor or momentum model, thus suggesting that these models are unsuitable for pricing our four profitability portfolios. Only for the five-factor model the null hypothesis of the test cannot be rejected giving support to the use of a five-factor model as an appropriate model to price profitability portfolios in Latin America.

Insert Table 9 here

6. Concluding remarks

In this paper we examine whether firm profitability has the ability to predict stock returns in Latin America. We find that operating profitability (either scaled by the book value of equity or by total assets) has a positive and significant effect on stock returns based on evidence of univariate portfolio sorts on profitability and bivariate portfolio sorts on profitability and several relevant stock characteristics that have been shown to predict returns. Furthermore, in Fama and MacBeth regressions (1973), loadings on profitability are positive and highly significant after controlling for book-to-market, size, reversal, and momentum effects. On the whole, our findings are robust to several methodological changes and in particular, whether we examine the profitability effect on the two main sub-regional markets (Brazil and MILA), or whether we focus in the segment of small (or below median market cap) or large (above median cap) stocks. By and large, when we try to dilute the influence of small stocks on our inferences (following the findings of Hou et al. (2015) in which many of the many documented "anomalies" are likely to be overstated by equally-weighting stocks), we still find a positive profitability effect in the region. Inspired by recent literature that proposes the inclusion of a profitability factor as a systematic risk factor (Fama and French (2015a), Novy-Marx (2016)), we study the capability of a five-factor model to explain returns of profitability portfolios in Latin America. We compare the pricing power of the recent five-factor model with several popular factor models (CAPM, Fama and French (1993) three-factor model and Carhart (1997) model). Five-factor alphas to profitability portfolios tend to be lower and less significant when compared to alphas produced by other factor models. Furthermore, the five-factor model is the only model that produces intercepts jointly indistinguishable from zero (using the GRS test). All in all, our findings are consistent with the existence of a priced profitability factor. For future research it would be interesting to expand the evidence on whether the five-factor model is able to price (in Latin America or other emerging markets) not only profitability portfolios, but also other portfolios formed on stock characteristics such as idiosyncratic volatility (Ang et al. (2006)), or illiquidity (Amihud, Kang, and Zhang (2015)). In addition, it would be worthwhile to test whether profitability measures related to cash profits (as in Ball et al. 2016) do have a stronger predictive ability on stock returns than profitability measures based on accounting accruals (as those analyzed here) in Latin America's main stock markets.

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8. Tables

Table 1 Descriptive statistics of Latin American stocks

	RET	PR/AST	PR/BV	CAP	BM	MOM
2002	-0.013	0.010	0.023	0.299	1.744	-0.050
2003	0.033	0.012	0.027	0.225	1.721	0.134
2004	0.026	0.016	0.032	0.388	1.202	0.134
2005	0.009	0.020	0.041	0.499	0.875	0.117
2006	0.020	0.017	0.035	0.348	0.854	0.052
2007	0.014	0.018	0.038	0.481	0.645	0.168
2008	-0.034	0.017	0.037	0.664	0.569	-0.059
2009	0.040	0.013	0.030	0.350	0.966	0.119
2010	0.022	0.014	0.031	0.592	0.715	0.090
2011	-0.013	0.016	0.035	0.925	0.625	0.017
2012	0.011	0.015	0.032	0.891	0.743	0.009
2013	-0.008	0.013	0.028	0.898	0.714	-0.008
2014	-0.012	0.013	0.029	0.759	0.739	-0.027
2015	-0.028	0.012	0.026	0.626	0.783	-0.109
2016	0.024	0.011	0.024	0.453	0.980	-0.015

Note: This table includes median values by year of our main variables. RET refers to excess monthly returns (monthly returns minus the monthly risk-free rate). PR/AST (PR/BV) stands for operating profits (without subtracting research and development expenses) plus interest expense divided by the book value of assets (book value of equity). CAP (in USD billions) is the product of the number of common shares outstanding times the adjusted market price of a common share. BM (book-to-market ratio) is the ratio of the book value per share over the market value per share and MOM represents momentum returns (i.e., total returns from month t-2 to t-6).

Table 2 Returns and risk-adjusted returns to value-weighted profitability portfolios

Panel A. Portfolios sorted by PR/BV

	P1	P2	P3	P4	P4-P1
Returns	0.008	0.012**	0.014**	0.018***	0.010**
	[0.232]	[0.033]	[0.011]	[0.004]	[0.010]

	P1	P2	P3	P4	P4-P1
Alphas	-0.007***	-0.001	0.001	0.003*	0.011***
	[0.003]	[0.652]	[0.483]	[0.053]	[0.002]

Panel B. Portfolios sorted by PR/ASET

	P1	P2	P3	P4	P4-P1
Returns	0.008	0.011**	0.014***	0.018***	0.009**
	[0.208]	[0.037]	[0.009]	[0.005]	[0.026]

	P1	P2	P3	P4	P4-P1
Alphas	-0.007***	-0.001	0.002	0.003*	0.010***
	[0.003]	[0.521]	[0.463]	[0.083]	[0.004]

Note: This table reports returns and three-factor alphas or risk-adjusted monthly returns in U.S. dollars. P1 (Portfolio 1) includes the least profitable stocks and P4 the most profitable stocks. Column P4-P1 estimates returns and alphas for a long-short profitability portfolio. p-values for two-sided tests of zero alpha using standard errors by Newey et al. (1987) reported in brackets below alpha estimates. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels.

Table 3 Characteristics of profitability portfolios

	P1	P2	P3	P4
RET	0.001	0.004	0.009	0.007
PR/AST	-0.007	0.001	0.022	0.041
PR/BV	-0.018	0.019	0.046	0.096
CAP	0.203	0.588	0.829	0.973
BM	1.52	1.17	0.805	0.536
MOM	-0.001	0.025	0.053	0.069
ASSET GROWTH	0.040	0.077	0.098	0.121
Nr. of stocks.	56.3	55.8	55.6	56.0
Percentage of total CAP	0.10	0.20	0.30	0.40

Note: ASSET GROWTH stands for the annual growth rate of book assets (lagged by six months). Nr. of stocks is the average number of stocks included in a portfolio. Percentage of total CAP is the average market capitalization that each portfolio contributes to total capitalization in a month. The table reports characteristics of four operating profits portfolios. In every month we record the median value of a characteristic (see rows 1 to 7) of the stocks that belong to a given portfolio. We then average the time series of median values to get an estimate of the magnitude of the characteristic for the typical stocks in the four portfolios.

Table 4 Risk-adjusted returns to double sorted profitability portfolios

Panel A. Portfolios sorted by CAP and PR/BV

	P1	P2	High-Low
P1	-0.001	0.005***	0.006*
	[0.735]	[0.002]	[0.060]
P2	-0.003	0.002***	0.006**
	[0.122]	[0.004]	[0.038]
High-Low	-0.002	-0.003	
	[0.463]	[0.155]	

Panel B. Portfolios sorted by BM and PR/BV

	P1	P2	High-Low
P1	-0.004*	0.003***	0.007**
	[0.099]	[0.001]	[0.018]
P2	-0.002	0.002	0.004
	[0.320]	[0.538]	[0.347]
High-Low	0.002	-0.001	
	[0.359]	[0.714]	

Panel C. Portfolios sorted by MOM and PR/BV

	P1	P2	High-Low
P1	-0.002	0.000	0.003
	[0.377]	[0.857]	[0.453]
P2	-0.002	0.004***	0.005*
	[0.501]	[0.002]	[0.094]
High-Low	0.001	0.003	
	[0.869]	[0.231]	

Note: This table shows Carhart (1997) alphas from bi-dimensional independent sorts. In panel A we first sort stocks by CAP and then by PR/BV whether in panel B (C) we initially sort by BM (MOM) and then by PR/BV. More specifically, in each month we sort stocks on a control variable, and create two portfolios with stocks with below and above median values on the control variable respectively. Furthermore, we create two additional portfolios (comprising stocks with below (P1) and above (P2) median profitability values). We form and rebalance the four (from the intersection of the 2x2 portfolios) value-weighted portfolios in each month and report their alphas in the table. The final column in each panel of the table reports alphas for high-minus-low profitability portfolios (P2-P1) across different subsamples of the control variable (in rows) and profitability portfolios (in columns). P-values using Newey-West (heteroskedasticity and autocorrelation) standard errors computed with four lags are reported in brackets. ***, **, and * denote statistical significance at the 1, 5, and 10% levels, respectively.

Table 5 Fama MacBeth regressions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.011	0.009	0.010	0.007	0.010	0.008	0.009	0.006
	[0.175]	[0.262]	[0.187]	[0.359]	[0.224]	[0.332]	[0.242]	[0.423]
PR/BV	0.047***	0.055***	0.061***	0.045***				
	[0.002]	[0.001]	[0.000]	[0.000]				
CAP		-0.001**		-0.001		-0.001**		-0.001
		[0.038]		[0.202]		[0.034]		[0.241]
BM			0.003**	0.001			0.004***	0.001
			[0.015]	[0.683]			[0.004]	[0.425]
RET t-1				-0.019				-0.019
				[0.191]				[0.197]
MOM				0.026***				0.025***
				[0.000]				[0.001]
PR/AST					0.155***	0.176***	0.200***	0.151***
					[0.000]	[0.000]	[0.000]	[0.000]
R^2	0.013	0.027	0.023	0.084	0.014	0.028	0.024	0.085
T.	174	174	174	173	174	174	174	173
N	219	219	217	199	219	219	217	199

Note: This table shows regression coefficients using Fama MacBeth (1973) panel methodology. Excess monthly returns is the dependent variable in all eight specifications. R^2 stands for the mean adjusted R-squared of the monthly regressions. T. represents the number of monthly regressions. N. is the average number of firms in the cross-sectional regressions. p-values for two-sided tests of a zero regression coefficient using standard errors by Newey et al. (1987) are reported in brackets below coefficient estimates. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 6 Fama MacBeth regressions excluding the first CAP quintile

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.012	0.010	0.012	0.008	0.011	0.010	0.011	0.008
	[0.136]	[0.187]	[0.123]	[0.262]	[0.165]	[0.224]	[0.153]	[0.304]
PR/BV	0.038**	0.047***	0.053***	0.045***				
	[0.017]	[0.003]	[0.000]	[0.000]				
CAP		-0.003***		-0.002**		-0.003***		-0.002**
		[0.000]		[0.038]		[0.000]		[0.039]
BM			0.004**	0.001			0.004***	0.001
			[0.012]	[0.387]			[0.004]	[0.280]
RET t-1				-0.018				-0.019
				[0.207]				[0.178]
MOM				0.019**				0.019**
				[0.016]				[0.017]
PR/AST					0.113**	0.137***	0.163***	0.131***
					[0.016]	[0.002]	[0.000]	[0.000]
R^2	0.012	0.019	0.021	0.075	0.013	0.020	0.021	0.075
T.	174	174	174	173	174	174	174	173
N	178	178	176	164	178	178	176	164

Note: This table shows regression coefficients using Fama MacBeth (1973) panel methodology. Excess monthly returns is the dependent variable in all eight specifications. Each month we delete from our cross-sectional regressions those stocks at the bottom quintile of the (monthly) market cap distribution. R^2 stands for the mean adjusted R-squared of the monthly regressions. T. represents the number of monthly regressions. N. is the average number of firms in the cross-sectional regressions. p-values for two-sided tests of a zero regression coefficient using standard errors by Newey et al. (1987) are reported in brackets below coefficient estimates. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 7 Fama MacBeth regressions – sub-regional markets

Panel A. Brazil

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.013	0.011	0.014	0.012	0.013	0.010	0.014	0.011
	[0.204]	[0.264]	[0.169]	[0.226]	[0.239]	[0.311]	[0.189]	[0.247]
PR/BV	0.044**	0.053***	0.047**	0.038**				
	[0.025]	[0.002]	[0.011]	[0.049]				
CAP		-0.001		-0.002*		-0.002		-0.002*
		[0.140]		[0.073]		[0.134]		[0.099]
BM			0.002	0.001			0.002	0.001
			[0.255]	[0.682]			[0.148]	[0.601]
RET t-1				-0.050**				-0.051**
				[0.022]				[0.023]
MOM				0.036***				0.034***
				[0.000]				[0.000]
PR/AST					0.168**	0.193***	0.173**	0.146**
					[0.018]	[0.002]	[0.012]	[0.020]
R^2	0.025	0.041	0.039	0.104	0.024	0.040	0.036	0.103
T.	174	174	174	173	174	174	174	173
N	79	79	78	74	79	79	78	74

Panel B. MILA

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Intercept	0.010	0.008	0.008	0.006	0.009	0.006	0.006	0.005
	[0.156]	[0.280]	[0.236]	[0.369]	[0.197]	[0.356]	[0.358]	[0.405]
PR/BV	0.040	0.057*	0.074**	0.050*				
	[0.190]	[0.094]	[0.023]	[0.084]				
CAP		-0.001**		-0.000		-0.002**		-0.000
		[0.048]		[0.583]		[0.030]		[0.698]
BM			0.004***	0.001			0.005***	0.002
			[0.002]	[0.305]			[0.000]	[0.190]
RET t-1				0.021**				0.022**
				[0.046]				[0.040]
MOM				0.021***				0.020**
				[0.010]				[0.012]
PR/AST					0.145*	0.183**	0.253***	0.143*
					[0.051]	[0.025]	[0.005]	[0.060]
R^2	0.018	0.035	0.027	0.080	0.019	0.037	0.029	0.082
T.	174	174	174	172	174	174	174	172
N	141	141	139	125	141	141	139	125

Note: This table shows regression coefficients using Fama MacBeth (1973) panel methodology. Excess monthly returns is the dependent variable in all eight specifications. R^2 stands for the mean adjusted R-squared of the monthly regressions. T. represents the number of monthly regressions. N. is the average number of firms in the cross-sectional regressions. p-values for two-sided tests of a zero regression coefficient using standard errors by Newey et al. (1987) are reported in brackets below coefficient estimates. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 8. Portfolio sensitivities to Fama and French (2015a) factors

	Alpha	Beta	SMB	HML	RMW	CMA	R^2
P1	-0.002	1.152***	0.108	0.145**	-0.563***	-0.037	0.887
	[0.341]	[0.000]	[0.142]	[0.017]	[0.000]	[0.531]	
P2	0.000	0.940***	0.088**	0.133**	-0.117*	0.023	0.848
	[0.973]	[0.000]	[0.043]	[0.038]	[0.068]	[0.726]	
P3	0.002	0.923***	-0.105*	-0.191***	-0.054	0.052	0.882
	[0.366]	[0.000]	[0.056]	[0.001]	[0.461]	[0.410]	
P4	-0.000	1.125***	-0.040	0.015	0.362***	-0.004	0.931
	[0.923]	[0.000]	[0.575]	[0.810]	[0.000]	[0.937]	
P2-P1	0.002	-0.212***	-0.020	-0.012	0.446***	0.060	0.204
	[0.588]	[0.001]	[0.822]	[0.857]	[0.000]	[0.572]	
P3-P1	0.004	-0.229***	-0.213***	-0.336***	0.509***	0.089	0.353
	[0.270]	[0.000]	[0.007]	[0.000]	[0.000]	[0.412]	
P4-P1	0.002	-0.027	-0.148*	-0.130*	0.925***	0.033	0.576
	[0.400]	[0.448]	[0.057]	[0.053]	[0.000]	[0.614]	
P3-P2	0.002	-0.017	-0.193**	-0.324***	0.063	0.029	0.116
	[0.534]	[0.636]	[0.011]	[0.000]	[0.417]	[0.668]	
P4-P2	-0.000	0.185***	-0.128	-0.118	0.479***	-0.026	0.264
	[0.946]	[0.003]	[0.183]	[0.172]	[0.000]	[0.798]	
P4-P3	-0.002	0.202***	0.065	0.206**	0.416***	-0.055	0.239
	[0.544]	[0.000]	[0.419]	[0.013]	[0.000]	[0.575]	

Note: R^2 stands for the adjusted R-squared of the pricing regressions (see equation 5). p-values for two-sided tests of a zero regression coefficient using standard errors by Newey et al. (1987) are reported in brackets below coefficient estimates. ***, **, and * denote significance at the 0.01, 0.05, and 0.10 levels, respectively.

Table 9. GRS tests

	GRS-statistic	GRS-p-value
1-factor model	2.448	0.048
3-factor model	2.820	0.027
4-factor model	2.616	0.037
5-factor model	1.035	0.391

Note: The table reports the statistic and the p-value of the Gibbons, Ross, and Shanken (1989) test. The four tested pricing models are the CAPM (1-factor model), Fama and French (1993) 3-factor model, Carhart (1997) 4-factor model and Fama and French (2015) 5-factor model. The null hypothesis of the tests is that the intercepts (produced by each pricing model) of the four profitability portfolios are (jointly) indistinguishable from zero.