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The role of shorting, firm size, and time on market anomalies[☆]

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ABSTRACT

We examine the role of shorting, firm size, and time on the profitability of size, value, and momentum strategies. We find that long positions make up almost all of size, 60% of value, and half of momentum profits. Shorting becomes less important for momentum and more important for value as firm size decreases. The value premium decreases with firm size and is weak among the largest stocks. Momentum profits, however, exhibit no reliable relation with size. These effects are robust over 86 years of US equity data and almost 40 years of data across four international equity markets and five asset classes. Variation over time and across markets of these effects is consistent with random chance. We find little evidence that size, value, and momentum returns are significantly affected by changes in trading costs or institutional and hedge fund ownership over time.

1. Introduction

The returns to portfolios based on firm size, value, and momentum have presented a challenge to asset pricing theory since their discovery.[1] The pervasiveness, robustness, and magnitude of the return premia associated with size, value, and momentum has made them the focal point for discussions of market efficiency as well as critical inputs for describing the cross section of expected returns. These market anomalies have been shown to be robust in other stock markets, other time periods, and

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[1] Initially, these were challenges to the Capital Asset Pricing Model (CAPM). Small stocks on average outperform large stocks (based on market capitalization), even after adjusting for market exposure (Banz, 1981; Roll, 1983; Fama and French, 1992). Likewise, value stocks, with high ratios of fundamental or book value to market value (such as book-to-market equity, cash flow-to-price, or earnings-to-price ratios) outperform growth stocks, which have low book-to-price ratios (Stattman, 1980; Rosenberg, Reid, and Lanstein, 1985; DeBondt and Thaler, 1985; Fama and French, 1992; Lakonishok, Shleifer, and Vishny, 1994). There is also positive momentum in stock returns. Stocks that have done well relative to other stocks over the last six months to a year continue to outperform their peers over the next six months to a year, and stocks that have done relatively poorly continue to underperform (Jegadeesh and Titman, 1993; Asness, 1994; Fama and French, 1996; Moskowitz and Grinblatt, 1999; Grinblatt and Moskowitz, 2004).

other asset classes (Chan, Hamao, and Lakonishok, 1991; Hawawini and Keim, 1995; Fama and French, 1998, 2012; Rouwenhorst, 1998; Griffin, Ji, and Martin, 2003; Asness, Moskowitz, and Pedersen, forthcoming) and have motivated the use of empirical asset pricing models that incorporate their returns (Fama and French, 1993, 2012; Carhart, 1997; Asness, Moskowitz, and Pedersen, forthcoming). The vast literature on these anomalies has generated a wide debate as to the underlying explanations for these return premia, which generally fall into two categories: rational risk-based models or behavioral theories. Also, a lack of consensus exists on the implementability of these strategies in practice. Both of these issues are paramount to discussions of market efficiency with respect to these anomalies.

Given the disparate views in the literature, we take stock of the empirical evidence of these market anomalies, to shed some light on these issues. We investigate three questions. First, how important is short selling to the profitability of these strategies? Second, what role does firm size play in the efficacy of these investment styles? Third, how have the returns to these strategies and the role of size and shorting varied over time? The importance of size, shorting, and time to the profitability of these strategies helps identify possible explanations as well as implementation costs associated with each anomaly. Without having to specify a trading cost model, which is investor specific, we acknowledge that small stocks are more costly and more difficult to trade and that shorting is more costly and more constrained. Arbitrage activity and capital are, therefore, likely to be more limited in small stocks and when shorting. Consistent with this view, many behavioral theories suggest stronger returns among smaller, less liquid securities and when there is negative news (Hong and Stein, 1999; Hong, Lim, and Stein, 2000; Lee and Swaminathan, 2000). How these effects have evolved over time could also help reveal what drives these anomalies. We examine how these effects have varied with changes to trading costs and institutional ownership over time, including the surge in hedge fund activity over the last two decades.

We examine the role of shorting from two perspectives: the value added from short selling of assets in a long-short portfolio and the value added from underweighting stocks relative to a benchmark (e.g., the market portfolio). Because short positions are generally more costly to maintain than long positions and because some investors are restricted from taking short positions (e.g., mutual funds and institutions) the net of trading cost returns could be substantially lower and not accessible to many investors, if shorting is an important driver of the profits to these strategies.

The role of firm size also plays a dual part in our study. First, we examine the return premium associated with size. Second, we examine the interaction between firm size and the return premia to value and momentum, including the interaction of firm size with the importance of shorting for these strategies. If the bulk of the returns to these strategies is concentrated among small or micro-cap stocks, then the fraction of the market affected by these anomalies could be small. Moreover, trading costs are typically highest among the smallest stocks, and small stocks are the most difficult and costly to short. Hence, the interaction between firm size and the other anomalies provides insight into the implementation costs of these strategies.

Using data over the last 86 years in the U.S. stock market (from 1926 to 2011) and over the last four decades in international stock markets and other asset classes (from 1972 to 2011), we find that the importance of shorting is inconsequential for all strategies when looking at raw returns. For an investor who cares only about raw returns, the return premia to size, value, and momentum are dominated by the contribution from long positions. Shorting only matters if investors care about returns relative to a benchmark, such as the market portfolio. Looking at market-adjusted returns (market alphas), long positions comprise the bulk of the size premium, capture about 60% of the value premium, and comprise half of the momentum return premium. Long-only versions of value and momentum deliver positive and significant alphas relative to the market.

Looking across different size firms, we find that the momentum premium is present and stable across all size groups. Little evidence exists that momentum is substantially stronger among small cap stocks over the entire 86-year US sample period. The value premium, meanwhile, is largely concentrated only among small stocks and is insignificant among the largest two quintiles of stocks (largest 40% of NYSE stocks).[2]

The contribution to value and momentum profits from shorting varies with firm size. Shorting becomes less (more) important for momentum and more (less) important for value strategies as firm size decreases (increases). However, across all size groups, we cannot reject that the abnormal profits to value and momentum trading are generated equally by long and short positions.

We examine the robustness of these findings over time and in relation to time series variation in trading costs, institutional ownership, and hedge fund assets. First, we find that significant momentum returns are present across size categories in every 20-year subsample we examine, including the most recent two decades that followed the initial publication of the original momentum studies. Moreover, the findings of Hong, Lim, and Stein (2000) and Grinblatt and Moskowitz (2004) that momentum is markedly stronger among small cap stocks and on the short side seems to be sample specific. Outside of the samples studied in those papers [most notably, 1980 to 1996, the sample period covered in Hong, Lim, and Stein (2000)], we find no evidence that momentum is stronger among small stocks or from shorting, and, over the entire period that includes those samples, no significant difference emerges in momentum returns across size groups or from shorting. Returns to value investing, however, are consistently stronger among small cap stocks in every subperiod and are largely nonexistent among large cap

[2] We follow the academic literature and, specifically, Fama and French (1992, 2008, and 2010) in forming portfolios that use all publicly traded stocks on the NYSE, Amex, and Nasdaq. This means our smallest size groupings of stocks contain mostly micro-cap stocks that could be difficult to trade and implement in a real-world portfolio. The smallest grouping of stocks contain firms that are much smaller than firms in the Russell 2000 universe.

stocks in three of the four subperiods we examine. We find no evidence that returns to these strategies have changed over time or that the contribution from long versus short positions has changed over time.

Second, we examine how the returns to size, value, and momentum have varied with changes in trading costs and institutional ownership over the last century, including hedge fund participation over the most recent two decades. While we find some weak evidence that momentum returns rise as trading costs rise, particularly among small stocks, little evidence exists that trading cost changes have had a material effect on these return premia. Likewise, we find little to no relation between institutional ownership or hedge fund growth and these return premia, other than a decline in the size premium with increased institutional ownership, consistent with Gompers and Metrick (2001).

Finally, we also examine these strategies across four international stock markets and five other asset classes over a 40-year period. Additional evidence from these other markets confirms the existence of value and momentum return premia and similarly finds an equal contribution of long and short positions to those returns.

Our findings shed new light on the vast literature on size, value, and momentum effects in asset pricing. Hong, Lim, and Stein (2000) and Grinblatt and Moskowitz (2004) also examine momentum returns across firm size and the long versus short side contributions to momentum profits. Their conclusions that momentum is stronger among small cap stocks and that two-thirds of the profits come from shorting are not robust in our larger sample. We find that momentum returns are largely unaffected by size and that the short side is no more profitable than the long side over our longer 86-year sample period and in eight other markets and asset classes. Fama and French (2012) examine value and momentum in international stock markets from 1990 to 2009 across size groupings. They find that both value and momentum premia are present in all markets, with the exception of momentum in Japan, and that value and momentum premia exist in all size groups, with return premia being stronger as size decreases.[3] Over our longer 86-year sample period, we find no evidence that momentum declines with firm size, but we do find consistent evidence that value returns are weaker for larger stocks.

The rest of the paper is organized as follows. Section 2 describes our data and portfolios. Section 3 analyzes the importance of shorting and time on size, value, and momentum strategies. Section 4 examines the role of firm size on value and momentum return premia as well as the interaction between firm size and the importance of shorting. Section 5 analyzes how the importance of shorting and firm size varies over time and whether variation in trading costs or institutional ownership and hedge fund participation has impacted these strategies over time. Section 6 examines other equity markets and asset classes. Section 7 concludes.

2. Data

Most of the analysis in this study pertains to US equity portfolios over the period July 1926 to December 2011 for value and size portfolios and over the period January 1927 to December 2011 for momentum portfolios. We also examine international equity portfolios and portfolios of other asset classes that include country equity indices, government bonds, currencies, and commodities futures over the period February 1972 to December 2011.

2.1. US equity portfolios

Most of the data for US equity portfolios comes from Ken French's data library (French, 2012) and is derived from underlying stock returns data from the Center for Research in Security Prices (CRSP). We examine value-weighted and equal-weighted decile and quintile portfolios formed on size (market capitalization), value (book-to-market equity, BE/ME), and momentum (past 12-month return, skipping the most recent month), as well as five-by-five quintile double sorted portfolios formed sequentially on size then value and also size then momentum (i.e., dependent sorts on size).

For each anomaly, we use a single, simple, and fairly standard characteristic to sort stocks into portfolios based on size, value, and momentum. There are several ways to measure each anomaly and form portfolios. For value, we use the standard book-to-market equity ratio, BE/ME, as measured by Fama and French (1992, 1993, 1996, 2008), which is the book value of equity of the stock from the previous year-end divided by the market value of equity at that time. Other value measures, such as book values divided by more recent market values as in Asness and Frazzini (2012), or those considered by Lakonishok, Shleifer, and Vishny (1994) and Fama and French (1996), such as earnings-to-price ratio (E/P), cash flow-to-price ratio (C/P), dividend yield (D/P), and long-term reversal [the negative of the past 60-month return, -*Ret*(1,60), as first used by DeBondt and Thaler (1985)], could yield slightly different results but should generally be consistent. We provide some robustness tests using these alternative measures in the Appendix.

For momentum, we simply use the standard past 12-month return skipping the most recent month, *Ret*(2,12). Other momentum measures such as Novy-Marx (2012), who advocates that *Ret*(7,12) is a stronger predictor of returns than *Ret*(2,6),[4] the disposition effect momentum measures of Grinblatt and Han (2005) and Frazzini (2006), or earnings momentum measures of Chan, Jegadeesh, and Lakonishok (1996) could also yield slightly different results but should be largely consistent with our findings. In this paper, we use a single variable for value (BE/ME) and momentum [*Ret*(2,12)] to maintain uniformity across time and markets. These measures are available over the longest

[3] See Asness (2011) for a counter view of whether momentum exists in Japan. Asness (2011) argues that, relative to a value benchmark or the Fama and French (2012) three-factor model in Japan, momentum exhibits a robust and sizable alpha. The mean-variance frontier of Japanese stocks contains a significant positive weight on momentum.

[4] However, Novy-Marx (2012) finds that one cannot reject whether *Ret*(7,12) is a better predictor than *Ret*(2,12) in his sample. Hence, both measures seem to capture the same phenomenon. Moreover, Goyal and Wahal (2012) find that *Ret*(7,12) is not a better predictor than *Ret*(2,6) outside of the US in 34 out of 35 countries.

time period from 1926 to 2011 and are the most commonly used measures in the literature.[5]

The size decile portfolios are formed by ranking stocks on their market capitalization in June of the previous year and forming ten equal groups based on NYSE breakpoints. All publicly traded stocks on the NYSE, Amex, and Nasdaq are then assigned based on their June market caps to one of these decile groups and the returns to each decile are computed over the following year.[6] Two sets of decile portfolio returns are computed: value-weighting the stocks in each decile and equal weighting them. The same procedure is used to form decile portfolios based on value, in which firms are ranked each June based on BE/ME instead of firm size, and decile portfolios for momentum, in which stocks are ranked each month on their past 12-month return, skipping the most recent month (cumulative return from month *t*-12 to *t*-2).

The five-by-five double-sorted size and value and size and momentum portfolios are formed similarly, except that size quintile portfolios are formed first (using NYSE breakpoints) and value and momentum portfolios are formed dependently within each size quintile. For more details on the construction of these portfolios, see Ken French's data library (French, 2012). We use the 25 size-value and 25 size-momentum portfolios to examine the results for value and momentum across different size stocks. To give a sense of the size groupings, in December 2011, the average size stock in the largest size group, Quintile 5, is just over $36 billion. The average size stock in the Russell 1000 at the end of 2011 is about $14 billion. The second largest size group, Quintile 4, has an average size of $4.8 billion at the end of 2011. The average size stock in the Russell Midcap index at that time is around $5 billion. Size Quintile 3 has an average market cap of about $2 billion, which is larger than the average size firm in the Russell 2000 index at that time, which is under $800 million. The smallest size groupings, Quintiles 2 and 1, have average market caps of $855 million and $156 million, respectively. Size Quintile 2, therefore, contains stocks that are on average about the size of the average stock in the Russell 2000 index, and Quintile 1 contains essentially micro-cap stocks. Stocks in Quintiles 1 and 2 could face significant trading costs for any reasonably sized portfolio.

We also obtain the Fama and French factor portfolios RMRF, SMB, HML, and UMD, which are, respectively, the returns to the CRSP value-weighted market portfolio in excess of the Treasury bill rate (RMRF), a small minus big (SMB) factor that is long the smallest half of firms and short the largest half of firms, a high minus low (HML) book-to-market factor, and an up minus down (UMD) momentum factor.[7] We also examine just the long side of these factors: portfolios S, H, and U, which are, respectively, a value-weighted portfolio of the smallest half of stocks based on NYSE breakpoints, the average of the two highest 30% BE/ME portfolios among small and large stocks, and the average of the two highest 30% momentum portfolios among small and large stocks.

2.2. International equity and other asset class portfolios

International equity and other asset class portfolios are obtained from Asness, Moskowitz, and Pedersen (forthcoming). International equity returns are from Datastream and are aggregated across four regions: the US, UK, Europe (excluding UK), and Japan. All returns are denominated in US dollars. Data from the US and UK cover the period February 1972 to December 2011; Europe and Japan, February 1974 to December 2011. Equity index return data come from MSCI for 18 developed markets covering the period January 1978 to December 2011. International government bond returns come from Bloomberg and Datastream covering ten developed markets from January 1982 to December 2011. Currency returns for ten developed countries come from Bloomberg for the period January 1979 to December 2011. Commodity futures returns on 27 commodities come from a variety of exchanges and cover the period January 1972 to December 2011. Details on the source of these returns and their construction can be found in Asness, Moskowitz, and Pedersen (forthcoming).

We obtain the value and momentum portfolios in each of these markets and asset classes used by Asness, Moskowitz, and Pedersen (forthcoming), who divide each market's or asset classes' securities into three equal groups based on value or momentum rankings, in which momentum is defined as the past 12-month return on each security, skipping the most recent month's return, and value is defined as book-to-market equity for stocks and stock indices and by the negative of the past 60-month return of the security for other asset classes.[8]

[5] Other measures of value, such as E/P or C/P, are available only beginning in 1951 and other measures of momentum, such as the disposition effect measures, are limited by the availability of volume data. Assessing the differential effects on returns from using different measures of value and momentum is beyond the scope of this paper, though we discuss the robustness of our results to other measures when appropriate.

[6] Fama and French (1993, 1996, and 2008) use NYSE breakpoints so that each decile contains an equal number of NYSE stocks. Because Amex and Nasdaq contain much smaller stocks on average, this prevents the deciles from becoming exchange specific and, therefore, for comparisons across deciles to be confounded by exchange effects. In addition, because Amex begins in 1963 and Nasdaq in 1973, use of NYSE breakpoints provides more consistency over time to allow for more meaningful comparisons to be made prior to 1963.

[7] SMB and HML are formed by first splitting the universe of stocks into two size categories (S and B) using NYSE market cap medians and then splitting stocks into three groups based on book-to-market equity [highest 30% (H), middle 40% (M), and lowest 30% (L), using NYSE breakpoints]. The intersection of stocks across the six categories are value-weighed and used to form the portfolios SH (small, high BE/ME), SM (small, middle BE/ME), SL (small, low BE/ME), BH (big, high BE/ME), BM (big, middle BE/ME), and BL (big, low BE/ME), where SMB is the average of the three small stock portfolios (1/3SH+1/3SM+1/3SL) minus the average of the three big stock portfolios (1/3BH+1/3BM+1/3BL) and HML is the average of the two high book-to-market portfolios (1/2SH+1/2BH) minus the average of the two low book-to-market portfolios (1/2SL+1/2BL). UMD is constructed similarly to HML, in which two size groups and three momentum groups [highest 30% (U), middle 40% (M), lowest 30% (D)] are used to form six portfolios and UMD is the average of the small and big winners minus the average of the small and big losers.

[8] The motivation for using the negative past five year return as a value indicator comes from DeBondt and Thaler (1985, 1987) and Fama and French (1996), who show that the past five year performance of stocks is a signal of value. Asness, Moskowitz and Pedersen (forthcoming) find that stock portfolios created from past five year returns are on average 0.86 correlated with portfolios created from other value measures such as BE/ME.

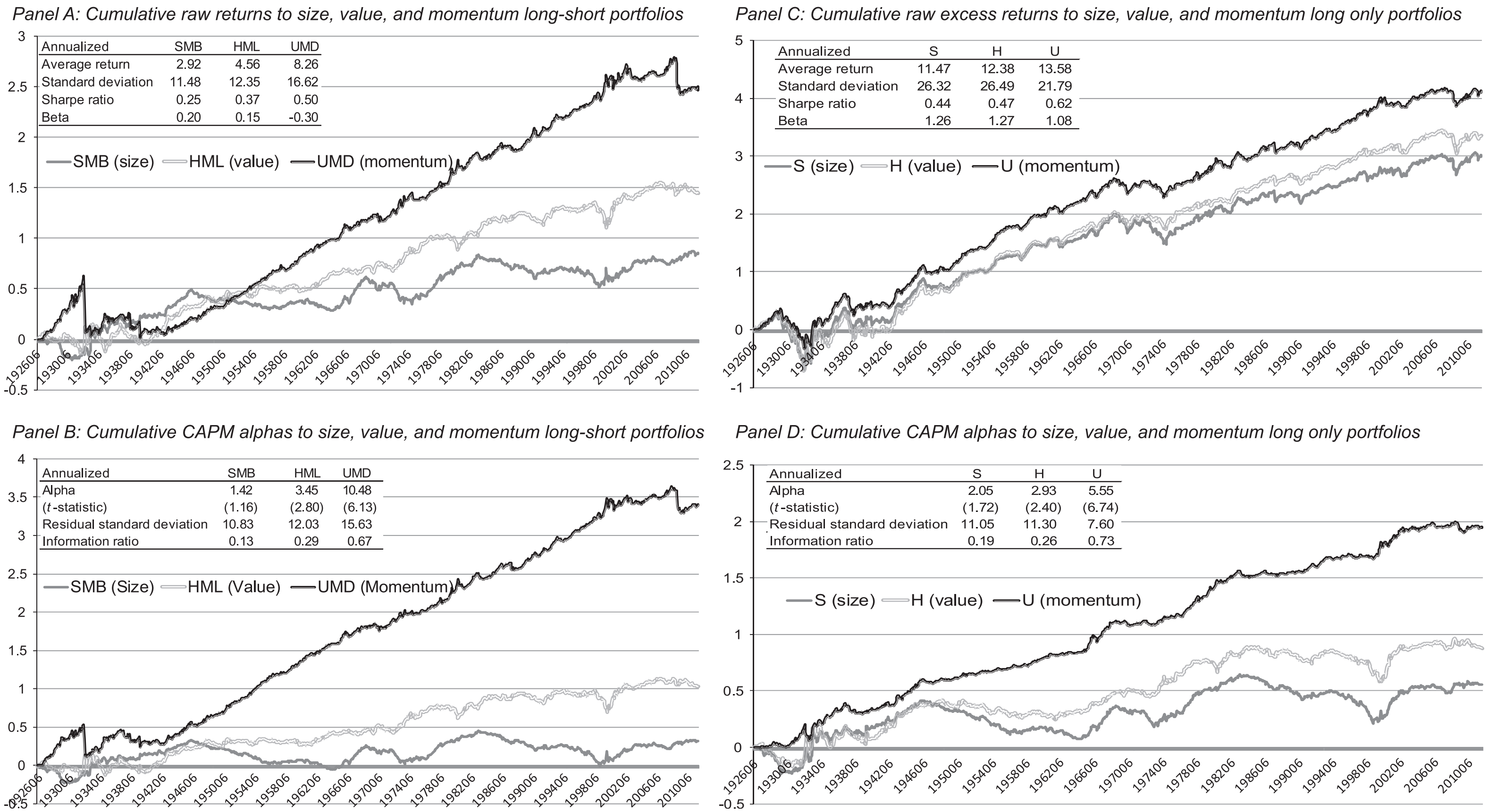

Fig. 1. Cumulative returns to size, value, and momentum portfolios. Plotted are the monthly cumulative sum of log returns on size, value, and momentum portfolios from July 1926 (January 1927 for momentum) to December 2011. Panels A and B plot the cumulative raw returns and Capital Asset Pricing Model (CAPM) alphas (with respect to the value-weighted market index), respectively, of long-short portfolios, and panels C and D plot the raw returns and alphas, respectively, of long-only portfolios. SMB=small minus big; HML=high minus low; UMD=up minus down.

Securities are then value weighted within each group in the case of individual stocks and equal weighted in the case of other asset classes. The spread in returns between the portfolios representing the top and bottom third of securities capture the value and momentum premia within each market or asset class.

3. The importance of shorting and time

We examine how important short selling and time are to the profitability of size, value, and momentum strategies.

3.1. Fama and French factor portfolios

We begin by looking at the profits to size, value, and momentum long-short strategies from the Fama and French factor portfolios. Fig. 1, Panel A plots the cumulative (sum of log) returns of the Fama and French portfolios SMB, HML, and UMD. Over the common 1927 to 2011 time period, returns to momentum are highest, averaging 8.26% per year with an annual standard deviation of 16.6% (an annual Sharpe (Sharpe, 1964) ratio of 0.50), followed by value, averaging 4.56% per year with 12.4% annual volatility (Sharpe ratio of 0.37), and then size, averaging 2.9% per year with 11.5% standard deviation (Sharpe ratio of 0.25).

Fig. 1, Panel B plots the cumulative capital asset pricing model (CAPM) alphas of SMB, HML, and UMD, in which CAPM betas are estimated unconditionally over the entire sample period by running a time series regression of each portfolio's monthly returns on the CRSP value-weighted market index return in excess of the T-bill rate. SMB exhibits an insignificant 1.42% per year alpha that is statistically indistinguishable from zero (*t*-statistic = 1.16). HML has a 3.45% per year alpha that is 2.8 standard errors from zero, and UMD has a 10.48% per year alpha that is more than 6 standard errors from zero. Comparing Fig. 1, Panels A and B, adjusting for market beta decreases the size and value premia but increases the momentum premium.

Fig. 1, Panel C plots the cumulative raw excess returns of the long-only components of the Fama and French factor portfolios: S, H, and U. The same ranking of performance among the three investment styles is present. The long-only momentum portfolio generates 13.6% (in excess of T-bills) per year on average with a 21.8% standard deviation (Sharpe ratio of 0.62). The long-only value portfolio produces 12.4% (in excess of T-bills) per year with a higher 26.5% volatility (Sharpe ratio of 0.47), and the long-only size portfolio generates 11.5% (in excess of T-bills) per year with 26.3% standard deviation (Sharpe ratio of 0.44). Because the long-only portfolios are dominated by general stock market exposure, we also report the unconditional market betas of each portfolio. Small stocks and value stocks have betas of 1.26 and 1.27, respectively, and recent 12-month winners have a beta of 1.08. Fig. 1, Panel D plots the cumulative alphas of the long-only portfolios relative to the market portfolio. Size and value exhibit 2.05 and 2.93% per year alphas,

Table 1
Capital Asset Pricing Model (CAPM) alphas of size, value, and momentum portfolios over time.

Reported are the CAPM alphas (and *t*-statistics of those alphas) of the Fama and French factor portfolios SMB (small minus big), HML (high minus low), and UMD (up minus down), representing size, value, and momentum long-short portfolio returns, respectively, as well as the long and short sides of each portfolio, for the full sample period from July 1926 (January 1927 for momentum) to December 2011 and six subperiods: July 1926 (January 1927 for momentum) to December 1962, January 1963 to December 2011, July 1926 (January 1927 for momentum) to December 1949, January 1950 to December 1969, January 1970 to December 1989, and January 1990 to December 2011. All alphas are annualized and expressed as percents and are calculated estimating market betas over each sample period separately.

	CAPM Alphas (*t*-stats)						
	1926–2011	1926–1962	1963–2011	1926–1949	1950–1969	1970–1989	1990–2011
Size							
Small	2.05	0.70	3.08	3.12	1.72	2.62	2.27
	(1.72)	(0.33)	(2.30)	(1.01)	(1.03)	(1.29)	(1.07)
Big	0.65	−0.01	1.19	0.26	0.77	1.72	0.90
	(1.40)	(−0.01)	(2.49)	(0.25)	(1.66)	(3.41)	(0.96)
SMB	1.42	0.71	1.92	2.86	0.99	0.90	1.39
	(1.16)	(0.37)	(1.29)	(1.02)	(0.59)	(0.42)	(0.56)
Value							
High	2.93	0.73	4.72	2.71	2.67	5.91	2.98
	(2.40)	(0.33)	(4.21)	(0.86)	(1.72)	(3.50)	(1.66)
Low	−0.58	0.05	−1.07	1.21	−0.40	−2.23	−1.04
	(−0.87)	(0.05)	(−1.27)	(0.80)	(−0.41)	(−1.82)	(−0.75)
HML	3.45	0.68	5.74	1.50	3.04	8.10	3.95
	(2.80)	(0.33)	(4.14)	(0.51)	(1.82)	(4.10)	(1.67)
Momentum							
Up	5.55	5.79	5.45	6.69	5.43	5.08	4.68
	(6.74)	(4.34)	(5.16)	(3.36)	(4.32)	(3.55)	(2.71)
Down	−4.94	−6.44	−3.76	−3.61	−4.83	−4.39	−4.19
	(−3.74)	(−2.89)	(−2.43)	(−1.14)	(−3.28)	(−2.03)	(−1.54)
UMD	10.48	12.23	9.21	10.29	10.26	9.47	8.87
	(6.13)	(4.49)	(4.35)	(2.61)	(5.21)	(3.32)	(2.38)

respectively, and momentum has a 5.55% alpha. Moreover, the residual volatility of the momentum portfolio (7.60%) is smaller than that of size (11.05%) or value (11.30%). Hence, long-only momentum produces an annual information ratio almost three times larger than value or size (0.73 information ratio for momentum compared with only a 0.26 information ratio for long-only value and 0.19 for long-only size).

Fig. 1, Panel D indicates that a long-only version of size produces a marginally significant abnormal return, but that long-only versions of value and momentum deliver significant abnormal returns relative to the market. Hence, for an investor constrained to hold long-only investments, size, value, and momentum still offer additional return premia above the general market return, in which momentum offers the largest premium and the lowest residual risk.

Table 1 reports the CAPM alphas of the long, short, and long minus short returns associated with size, value, and momentum over various subperiods, using the Fama and French factor portfolios. The first column reports results for the full sample from 1926 (or 1927 in the case of momentum) to 2011, the second column reports results up to 1962 before the introduction of Amex (1963) and Nasdaq (1973) stocks to CRSP, and the third column reports results from 1963 to 2011. Beginning with size, there is no significant alpha for SMB over any of these time periods, though the long-side, S, exhibits a marginally significant alpha of 2.05% per year over the full sample period (t-statistic=1.72) and a significant alpha of 3.08% (t-statistic=2.30) from 1963 to 2011. HML exhibits a significant CAPM alpha of 3.45% per year over the entire sample period, but all of it comes from the second half of the sample, in which there is a 5.74% per year alpha (t-statistic=4.14). Before 1963, however, HML exhibits an insignificant 0.68% alpha. This result is consistent with Fama and French (2006), who also find that the CAPM captures HML in the pre-1962 period. Momentum, as proxied by UMD, exhibits a robust and consistent alpha over both periods: 12.23% from 1927 to 1962 and 9.21% from 1963 to 2011.

Looking at the long and short sides of these strategies, SMB is dominated by long positions; HML is driven mostly, but not entirely, by the long side; and UMD appears to be equally driven by long and short profitability. Focusing only on the long side of each strategy, momentum continues to produce larger and more consistent alphas than size or value, and each produce positive alpha only in the second half of the sample.

The remaining four columns of Table 1 report results across four subperiods split into roughly equal 20-year intervals. Looking at these finer time slices, there is no significant size premium in any subperiod after adjusting for the market. The value premium is positive in every subperiod but is only statistically significant at the 5% level in one of the four 20-year periods, from 1970 to 1989. The momentum premium, however, is positive and statistically significant in every subperiod, producing reliable alphas that range from 8.9% to 10.3% per year over the four subperiods.

3.2. Decile portfolios

To further examine the role shorting plays in the efficacy of size, value, and momentum strategies, we examine portfolios based on finer sorts of these characteristics. Table 2 reports the average raw returns in excess of T-bills, Sharpe ratios, and market (CAPM) alphas of value-weighted decile-sorted portfolios based on size, value, and momentum over the period July 1926 (January 1927 for momentum) to December 2011. To gauge the importance

Table 2
Decile portfolios based on size, value, and momentum from July 1926 to December 2011.
Reported are the average raw returns in excess of the one-month T-bill rate, Sharpe ratios, and CAPM alphas of value-weighted decile portfolios formed on size, value (BE/ME), and momentum (past 12-month return, skipping the most recent month) over the period July 1926 (January 1927 for momentum) to December 2011. The difference between Deciles 10 and 1 (10-1) is also reported along with the differences between the average of Deciles 9 and 10 and the average of Deciles 1 and 2 (9-2), the average of Deciles 8 through 10 and the average of Deciles 1 through 3 (8-3), and the average of Deciles 7 through 10 and the average of Deciles 1 through 4 (7-4).

	Decile portfolios (value-weighted)										Differences			
	1	2	3	4	5	6	7	8	9	10	10-1	9-2	8-3	7-4
Size														
Raw excess	13.66	11.56	11.54	10.96	10.49	10.42	9.81	9.11	8.43	6.80	−6.86	−4.99	−4.14	−3.39
Sharpe	0.39	0.37	0.41	0.42	0.42	0.43	0.43	0.42	0.41	0.38	−0.26	−0.24	−0.24	−0.23
Alpha	2.97	1.26	1.63	1.67	1.30	1.47	1.25	0.90	0.54	−0.06	−3.03	−1.87	−1.49	−1.22
t-statistic	(1.22)	(0.71)	(1.18)	(1.38)	(1.34)	(1.83)	(1.85)	(1.67)	(1.29)	(−0.19)	(−1.15)	(−0.89)	(−0.86)	(−0.83)
Value														
Raw excess	6.65	7.68	7.85	7.58	8.38	8.88	9.00	10.83	11.66	12.54	5.89	4.93	4.28	3.57
Sharpe	0.33	0.40	0.42	0.36	0.43	0.41	0.39	0.45	0.44	0.39	0.26	0.28	0.28	0.28
Alpha	−0.75	0.48	0.90	−0.27	1.15	0.97	0.71	2.27	2.46	1.81	2.56	2.27	1.97	1.72
t-statistic	(−1.08)	(0.85)	(1.52)	(−0.39)	(1.58)	(1.18)	(0.70)	(2.00)	(1.91)	(0.95)	(1.11)	(1.26)	(1.28)	(1.32)
Momentum														
Raw excess	0.10	4.83	5.04	6.65	6.78	7.51	8.51	9.94	10.81	14.59	14.50	10.24	8.46	6.81
Sharpe	0.00	0.17	0.21	0.30	0.32	0.37	0.44	0.53	0.54	0.64	0.53	0.45	0.44	0.42
Alpha	−11.38	−5.04	−3.62	−1.46	−0.84	−0.05	1.33	3.02	3.65	7.04	18.42	13.55	11.25	9.13
t-statistic	(−6.00)	(−3.53)	(−3.17)	(−1.55)	(−1.04)	(−0.08)	(1.94)	(4.33)	(4.41)	(5.35)	(6.63)	(5.97)	(5.83)	(5.57)

of the long and short sides of these strategies, as well as any asymmetries in their returns, we report the differences between Deciles 10 and 1 (10-1), as well as the differences between the average of Deciles 9 and 10 and the average of Deciles 1 and 2 (9-2), 8 through 10 and 1 through 3 (8-3), and 7 through 10 and 1 through 4 (7-4). These differences are informative about whether the extreme portfolios behave any differently and how monotonic the relation is between these characteristics and returns.

As Table 2 shows, size, value, and momentum all exhibit a monotonic relation with average raw excess returns. Moving across the deciles generates consistently higher mean returns, and the spread in returns from Deciles 10-1 through Deciles 7-4 declines monotonically. However, the monotonic relation is not as evident when looking at Sharpe ratios because volatility tends to be U-shaped across the deciles, being highest for the two most extreme portfolios. The Sharpe ratios of size and value portfolios are flat across the deciles as a result, with the higher returns for the higher deciles being offset by higher volatility. Momentum exhibits a more monotonic relation across deciles with respect to Sharpe ratios, though the relation is flatter than it is for average returns, suggesting that volatility rises across the deciles but not as fast as average returns rise. Thus, there is added return per unit of volatility going across the momentum deciles, which is not evident for the size or value decile portfolios.

Looking at market alphas, no significant abnormal returns exist for size or value decile spreads over the entire 1926 to 2011 time period. In other words, over the full 86-year sample period, the CAPM seems to price well portfolios sorted on size and value (BE/ME). This result seems to contradict Fama and French (1992), who examine size and BE/ME portfolios from 1963 to 1990 and find that the CAPM cannot capture their returns. Over their sample period, we confirm their results. However, over the longer period from 1926 to 2011, the CAPM captures the returns to these portfolios well.

Alphas for momentum decile portfolio spread returns are statistically and economically large, indicating that, unlike size and BE/ME decile portfolios, momentum decile portfolio returns are unexplained by the CAPM over the full sample period.

Table 2 also highlights that long-only versions of size, value, and momentum produce positive alphas, but those of size and value are statistically weak. For momentum, however, winners deliver significant abnormal performance relative to the market, and this performance is not concentrated only among the securities with the most extreme characteristics. Deciles 8 and 9 also produce robust and significant positive alphas.

In the Appendix, we also report results for value-weighted decile portfolios sorted on other measures of value: E/P, C/P, D/P, -*Ret*(1,60), and a composite value index that is an equal-weighted average of portfolios sorted on these four measures of value and BE/ME. Unfortunately, data for E/P and C/P are available only from July 1951 to December 2011, so we cannot evaluate how these portfolios perform going back to 1926. As Table A1 in the Appendix shows, E/P and C/P each produce significant spreads in returns, and D/P and -*Ret*(1,60), which go back to 1927 and 1931, respectively, do not. Hence, of the five value measures we examine (including BE/ME), three produce insignificant spreads in returns and two produce significantly positive spreads. However, the two value measures, E/P and C/P, that produce positive spreads do so over the later 1951 to 2011 period. If we also examine the three other value measures [BE/ME, D/P, and -*Ret*(1,60)] over the 1951 to 2011 period, we obtain significantly positive alphas as well, except for -*Ret*(1,60). Thus, it appears that the efficacy of value strategies varies by time period, and, over the full sample period dating back to 1926, it is hard to find a reliable value premium among value-weighted decile portfolios.

As a final measure of value, we compute a composite index of all five value measures dating back to 1926 taking an equal-weighted average of all available value measures. The composite index is composed of just BE/ME, D/P, and -*Ret*(1,60) in the early part of the sample, and then E/P and C/P are included after July 1951. The spread in alphas from portfolios sorted on this composite value index are positive and significant at the 5% level over the full sample period from 1926 to 2011. Hence, evidence shows an abnormal value premium over the full century of data when taking an average of several value measures, but the value premium appears to be much weaker in the early half of the sample.

3.3. *What happened to the size effect?*

Tables 1 and 2 show no evidence of an abnormal size premium relative to the CAPM over the entire sample period or any of the 20-year subperiods. This result appears inconsistent with the Banz (1981) original discovery of an abnormal size effect. Two key differences between our results and Banz (1981) are sample period and methodology. Banz (1981) studies returns from 1936 to 1975 and primarily uses Fama and MacBeth (1973) cross-sectional regressions to examine the size effect. In Table A2 of the Appendix, we conduct analysis similar to Banz (1981) over both the entire sample period 1926 to 2011 and the Banz (1981) original sample period from 1936 to 1975.

Panel A of Table A2 reports the spread portfolio returns between the smallest and largest decile of stocks (based on NYSE breakpoints) over both periods. The first set of rows reports results for value-weighted decile portfolios identical to those used in Table 2. As the first rows of Panel A of Table A2 indicate, the size decile spread returns are only slightly higher over the Banz (1981) 1936 to 1975 time period, but there is still no evidence of a significant size effect. The next set of rows in Panel A of Table A2 repeats the analysis for equal-weighted portfolios. Banz (1981) uses Fama and MacBeth regressions on a set of 20 size- and beta-sorted portfolios. Fama and MacBeth regression coefficients can be interpreted as portfolio returns (see Fama, 1976), in which the securities are essentially weighted by their volatility (to minimize sum of residual squared errors), which makes them more tilted toward smaller securities than value weighting. As Panel A of Table A2 shows, the equal weighted decile portfolios, which are closer to what is obtained from a Fama and MacBeth regression, produce alphas that are

Table 3
Profitability of long and short side of value and momentum across size quintiles.

Reported are the average raw returns in excess of the one-month T-bill rate and CAPM alphas of return differences between Quintiles 5 and 1 of value and momentum-sorted portfolios across size quintiles. Stocks are first sorted into five size quintiles based on NYSE breakpoints and then sorted into value and momentum quintiles, respectively, for the two sets of 25 portfolios. The difference between the top and bottom quintiles (5 and 1) based on value and momentum sorts are reported within each size quintile. The t-statistics of the return differences, the returns of the long side only (Quintile 5) and its t-statistic (in parentheses), as well as the percentage of 5-1 profits coming from the long side and a t-statistic for whether the long side and short side contribution to profits is significantly different are also reported. The differences between size Quintiles 1 (smallest) and 5 (largest) are also reported. Results pertain to value-weighted portfolios over the sample period July 1926 (January 1927 for momentum) to December 2011.

	Smallest				Largest	
	Size 1	Size 2	Size 3	Size 4	Size 5	Size 1-Size 5
VALUE						
Returns						
5-1 spread	11.22	7.28	5.42	4.24	3.70	7.13
	(3.87)	(3.88)	(2.96)	(1.93)	(1.90)	(2.10)
Long side	16.45	14.26	13.48	12.36	11.01	6.07
	(4.58)	(4.34)	(4.17)	(3.67)	(3.86)	(2.74)
Percent long side	146.5	195.9	248.8	291.3	297.6	
Long=short (t-statistic)	(2.81)	(3.50)	(3.66)	(3.81)	(4.01)	
Alphas						
5-1 spread	12.99	6.38	4.63	1.54	2.19	10.58
	(4.52)	(3.41)	(2.53)	(0.74)	(1.14)	(3.21)
Long side	6.15	4.15	3.26	1.73	1.97	4.31
	(2.78)	(2.38)	(2.05)	(1.04)	(1.21)	(1.97)
Percent long side	47.4	65.1	70.4	112.9	89.9	
Long=short (t-statistic)	(0.15)	(0.67)	(0.89)	(1.18)	(1.15)	
MOMENTUM						
Returns						
5-1 spread	10.87	12.99	11.53	10.79	7.49	3.42
	(4.50)	(6.22)	(4.76)	(4.08)	(2.95)	(1.56)
Long side	18.76	17.17	15.61	14.98	10.98	7.79
	(5.59)	(5.71)	(5.89)	(6.09)	(4.95)	(3.35)
Percent long side	172.6	132.1	135.3	138.9	146.6	
Long=short (t-statistic)	(3.72)	(3.29)	(3.36)	(3.45)	(2.81)	
Alphas						
5-1 spread	13.12	15.30	14.48	14.19	10.24	2.88
	(5.59)	(7.66)	(6.32)	(5.72)	(4.23)	(1.31)
Long side	9.30	7.89	7.26	7.17	3.92	5.37
	(4.47)	(5.13)	(5.71)	(6.24)	(3.83)	(2.40)
Percent long side	70.9	51.6	50.1	50.5	38.3	
Long=short (t-statistic)	(1.34)	(0.17)	(0.02)	(0.09)	(1.78)	

almost three times higher than those from value-weighted deciles. Over the full sample period, the equal-weighted deciles produce an alpha of 8.4% per year with a t-statistic of 2.81, and from 1936 to 1975 they deliver an alpha of 6.8% (t-statistic of 1.62).

Panel B of Table A2 reports results from Fama and MacBeth regressions similar to those of Banz (1981). Using the 25 size and BE/ME portfolios from Ken French's data library (French, 2012), we regress the cross section of their returns every month on their full sample-estimated market betas and the log of their average market capitalization, log(size).[9] Coefficients are estimated every month (including a constant), and the time series average and time series t-statistic of the coefficients are computed in the style of Fama and MacBeth (1973). As Panel B of Table A2 shows, there is a consistent and significant negative size coefficient over both periods, indicating significantly higher average returns for small versus large stocks. The last set of rows in Panel B of Table A2 repeats the analysis using even more extreme portfolios—one hundred size and BE/ME sorted portfolios from Ken French's webpage. The Fama and MacBeth coefficients are similar and marginally significant over both periods.

Hence, the size effect emerges when considering more extreme exposure to small stocks, especially extremely small stocks, through either equal-weighted portfolios or Fama and MacBeth regressions. Less extreme exposure to size, through value weighting, for instance, does not produce a reliable size effect, and this evidence is consistent over the full sample period and the original time period studied by Banz (1981).

4. Interaction of firm size with value and momentum

Size plays a dual role in our study. In addition to studying the premium for size-sorted portfolios, we examine the interaction between firm size and value and firm size and

[9] Results are similar using rolling five-year beta estimates or post-ranking beta estimates as in Fama and MacBeth (1973) and Fama and French (1992).

momentum profitability. We analyze whether value and momentum premia are stronger among various sized stocks, whether the contribution to profits from longs and shorts differs across size groups, and whether any of these effects change over time. To evaluate the role firm size plays in the returns to value and momentum, we examine the 25 Fama and French size-value portfolios and the 25 size-momentum portfolios. We focus on value-weighted versions of each of these sets of 25 portfolios but also report results for equal-weighted portfolios.

4.1. Size-value portfolios

Table 3 reports the raw excess returns and market (CAPM) alphas of the 25 size and value and 25 size and momentum sorted portfolios estimated over the entire sample period. Returns and alphas are estimated from monthly returns but reported as annualized percentages. The 5-1 quintile spread return differences between high BE/ME and low BE/ME stocks and high and low momentum stocks within each size quintile, as well as the returns and alphas of just the long side [Quintile portfolio 5] within each size quintile are reported. Table 3 also reports the *t*-statistic of the mean returns and alphas and the percentage of 5-1 profits coming from the long side, including a formal statistical test of whether the profits from the long side are significantly different from 50%, an equal split between long and short contribution to profits. The last column of Table 3 reports the difference in mean returns and alphas between the smallest and largest quintile of stocks for both the 5-1 spread and long only (Quintile 5) portfolios of value and momentum.

As the top half of Table 3 indicates, the value premium declines monotonically with firm size. The raw return spread for high minus low BE/ME firms is 11.22% per year among the smallest quintile of stocks and 3.70% among the largest quintile of stocks. More than 100% of these return differences come from the long side. That is, an investor not worried about market exposure would be better off only taking the long side of these value strategies in each size quintile. However, adjusting for market exposure and market returns changes the picture somewhat. First, alphas of the 5-1 value spread in returns are also stronger among small stocks and are insignificant among large stocks. Second, looking at the long-only side of value strategies across size quintiles, the same pattern emerges: strong positive alphas for long-only value among small cap stocks and insignificant alphas among large caps. The difference in long-only value returns across size groups is economically and marginally statistically significant (*t*-statistic of 1.97), with a 4.31% per year difference in long-only value returns between the smallest and largest quintiles. Because the difference in long-short 5-1 value spread alphas is 10.58% between the smallest and largest size quintiles, this implies that shorting profits to value strategies vary more across size groups. The contribution of long side returns to value profitability increases as size increases. Among the smallest stocks, the long side of value contributes only 47% to total profits, but among the largest stocks the contribution of long positions is nearly 90%. Because shorting small, growth stocks could be expensive or difficult to implement, this could reduce the net of trading cost returns to a small value strategy in practice. While long positions comprise nearly the entire value premium among the largest stocks, the alpha for value among large cap stocks is not reliably different from zero.

4.2. Size-momentum portfolios

The bottom half of Table 3 shows that momentum exhibits strong predictability within each size quintile, with little evidence that momentum returns are stronger among small cap stocks. Momentum returns appear slightly stronger among the smallest quintile of stocks relative to the largest quintile of stocks, but the differences are small and insignificant. Moreover, the relation between momentum and size is not monotonic. The middle size quintiles exhibit the strongest returns, though, again, the differences across size are not statistically reliable. Comparing the returns with value and momentum across size, the momentum premium is consistently larger than the value premium in every size group except the smallest one, in which they are essentially equal.

Statistically significant differences exist in the returns and alphas of the long-only component of momentum across size quintiles, however. Long-only momentum is strongest among the smallest stocks and weakest among the largest stocks, though it is statistically and economically significant in each. As a percentage of total momentum profits, the long side contributes more than 100% of total profits in raw return space. That is, just like value, an investor not concerned with market risk should only go long winners and not short losers. However, adjusting for the market, the long side of a momentum strategy contributes more to its profitability among small stocks than large stocks. The long side contributes 71% of profits among small cap momentum and only 38% among large cap momentum. This is the opposite pattern exhibited by value. The importance of shorting for momentum strategies declines as firm size gets smaller. From an implementation perspective, this is good news because shorting small, losing stocks should be difficult and expensive. Hence, momentum has the nice feature that shorting losers becomes less important as firm size declines.

The results for momentum seem at odds with the conclusions drawn in Hong, Lim, and Stein (2000) and Grinblatt and Moskowitz (2004), who claim that momentum profits are stronger among small stocks and that shorting contributes more to momentum profits than the long side (about two-thirds of profits), particularly among small cap stocks. We find no discernible differences in momentum profits across size groups and that the importance of shorting for momentum declines instead of increases for small stocks. The key difference in our findings is primarily driven by sample period. Hong, Lim, and Stein (2000) examine returns from 1980 to 1996, and Grinblatt and Moskowitz (2004) examine returns from 1963 to 1999. We examine returns from 1927 to 2011. As shown in Table A3 of the Appendix, when looking over the same time period as Hong, Lim, and Stein (2000) and Grinblatt and Moskowitz (2004), we find results consistent with those studies. Momentum appears to be stronger among small caps and more driven by shorting. These results, however, are not borne out in other time periods out-of-sample. Looking over our entire sample

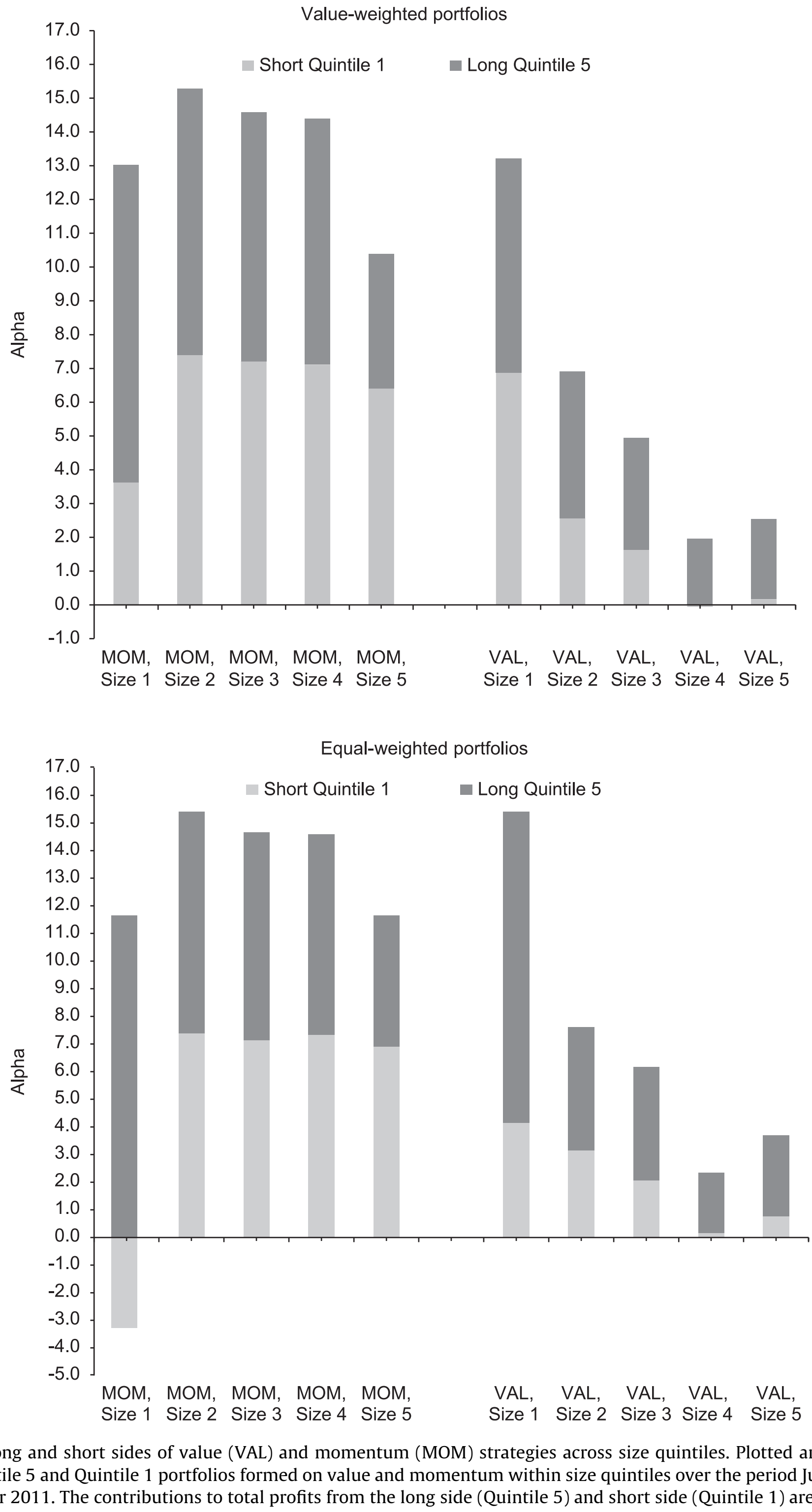

Fig. 2. Contribution of long and short sides of value (VAL) and momentum (MOM) strategies across size quintiles. Plotted are the CAPM alphas of the difference between Quintile 5 and Quintile 1 portfolios formed on value and momentum within size quintiles over the period July 1926 (January 1927 for momentum) to December 2011. The contributions to total profits from the long side (Quintile 5) and short side (Quintile 1) are highlighted on the graph. The top graph shows results from value-weighted portfolios; the bottom graph, equal-weighted portfolios.

period or out-of-sample from these studies, we find no statistical or economic evidence that the long and short side profits of a momentum strategy are different and no reliable differences in momentum returns across firm size groups.

In fact, the result that shorting small losers is a big component of momentum profitability, as concluded by Hong, Lim, and Stein (2000) and Grinblatt and Moskowitz (2004), seems to be unique to the 1980 to 1996 sample period studied by Hong, Lim, and Stein (2000). As Table A3 in the Appendix shows, removing the period 1980 to 1996 from the Grinblatt and Moskowitz (2004) sample (which is 1963 to 1999), we no longer find this result in their sample and we do not find it in the longer sample from 1927 to 2011. Even looking at the out-of-sample period from 2000 to 2011 following the Grinblatt and Moskowitz (2004) study, we find no evidence that momentum is stronger among small stocks or from shorting losers. Even within the subsamples, where there is a size-momentum interaction, it appears mostly driven by the short side. In the Hong, Lim, and Stein (2000) and Grinblatt and Moskowitz (2004) subsamples, no reliable difference is found in long-only momentum profits across size quintiles.[10] Only during the 1980 to 1996 period examined in Hong, Lim, and Stein (2000) is there any evidence that shorting small losers matters. Over the full sample that includes this period, however, no evidence shows that momentum is stronger among small stocks or from shorting. In fact, the importance of shorting gets weaker for small stocks.

More recently, Avramov, Chordia, Jostova, and Philipov (2007) claim that momentum profits are stronger among low credit–rated firms and nonexistent among highly rated firms, and Avramov, Chordia, Jostova, and Philipov (2012) claim that a host of anomalies, including momentum, derive the bulk of their profits from shorting high credit risk firms. These results seem at odds with our findings on the lack of a size-momentum interaction and the lack of importance of shorting. However, Avramov, Chordia, Jostova, and Philipov (2007) and Avramov, Chordia, Jostova, and Philipov (2012) study returns over the 1985 to 2003 and 1985 to 2008 sample periods, respectively, which, as we show, are periods over which a size-momentum interaction exists and shorting small (possibly distressed) firms appears more important. Over the full sample period we examine from 1926 to 2011, the size interaction and importance of shorting for momentum do not seem robust. However, because credit rating data are not available prior to 1985, we cannot say whether the momentum-credit rating interaction these authors find would be robust over the longer sample period we examine.

Fig. 2 summarizes our findings by plotting the 5-1 quintile spread in alphas for value and momentum strategies across size quintiles, with the contribution from the long and short sides highlighted on the graph. The long side is the alpha of Quintile 5, and the short side is the negative of the alpha of Quintile 1. The top figure reports results for value-weighted portfolios, and the bottom figure for equal-weighted portfolios. No discernible pattern emerges in momentum returns across size quintiles, even for equal weighted portfolios. (In fact, the smallest size quintile exhibits the lowest momentum returns among equal-weighted portfolios, and shorting losers contributes negatively to momentum profits among the smallest quintile of stocks when equal weighted.) But, there is a markedly declining value premium as size increases. Shorting contributes to less than 30% of the profits to a momentum strategy among small caps, about half of momentum among the middle size quintiles, and about 60% among the largest stocks. For value strategies, shorting makes up a little more than half of the premium in small caps for value-weighted portfolios and about a third for equal-weighted portfolios, with the importance of shorting declining as firm size increases. However, because the premium for value also declines substantially as firm size increases, the decline in the importance of shorting for a value strategy coincides with a much lower value premium. The patterns are similar for equal-weighted portfolios.

5. Variation over time

In this section, we examine the returns to size, value, and momentum over time and how the contribution to profits from the long and short side varies over time.

5.1. Time trends

Fig. 3 plots the CAPM alphas of value-weighted portfolios for value and momentum strategies within size quintiles over four subperiods: July 1926 (January 1927 for momentum) to December 1949, January 1950 to December 1969, January 1970 to December 1989, and January 1990 to December 2011. The momentum premium is strong in every subperiod and all size quintiles, including the most recent 20 years of data following the initial discovery and publication of the momentum effect in the early 1990s. This is consistent with the out-of-sample evidence on the robustness of momentum profits found in Jegadeesh and Titman (2001, 2005), Fama and French (2008, 2012), and Asness, Moskowitz, and Pedersen (forthcoming). As noted in Section 4, some differences are evident in the magnitude of the momentum premium across size quintiles over time. In the two most recent periods, momentum is stronger among small stocks, but in the two earlier subperiods no discernible relation exists between momentum profits and size.

Also, no evidence shows that shorting matters more for small stocks either. The only discernible difference across the size quintiles is that long-only momentum is somewhat stronger among small stocks, consistent with the evidence in Table A3 of the Appendix.[11] In summary, the relation between size and momentum and the importance of shorting found previously in the literature are due to one specific sample period and not robust out-of-sample.

Conversely, turning to value sorted portfolios, Fig. 3 shows a stronger value premium among small and micro-cap stocks in every subperiod, consistent with the previous literature (Fama and French, 1993, 1996, 2008; Grinblatt and Moskowitz, 2004). However, we find no reliable value

[10] This finding is also consistent with Grinblatt and Moskowitz (2004). Fama and French (2012) also find stronger momentum profits among small cap stocks in international data over the 1990 to 2009 time period.

[11] The introduction of Amex and Nasdaq stocks to the CRSP universe in 1963 and 1973, respectively, which introduces a large set of much smaller firms into the sample, is not responsible for these results. In the first half of our sample the universe of stocks is exclusively from the NYSE, and if we separate out NYSE stocks from Amex and Nasdaq stocks post-1963, we find similar effects (see appendix Table A4). Moreover, the use of NYSE breakpoints for the construction of our portfolios should also mitigate the effect of Amex and Nasdaq stocks in the sample.

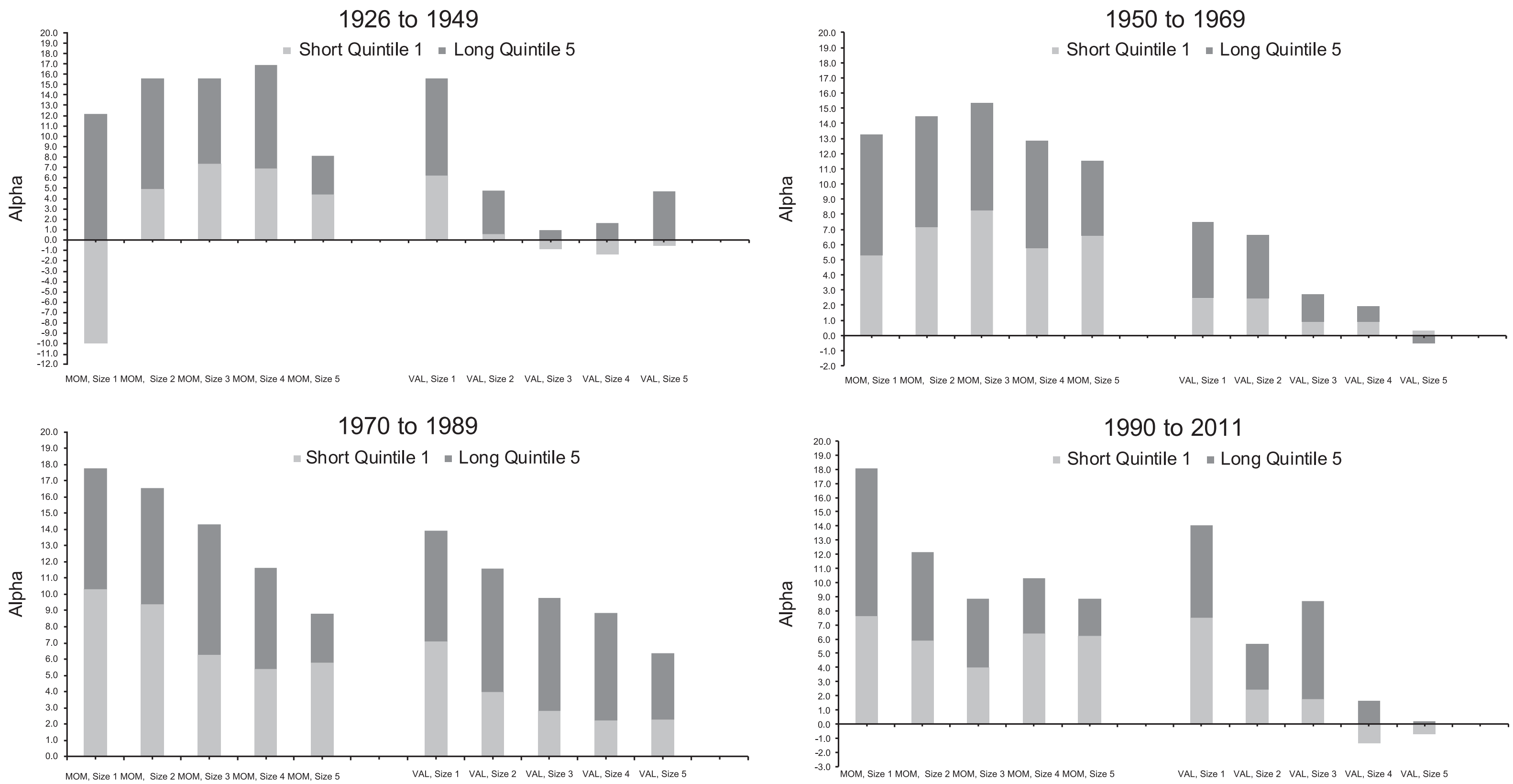

Fig. 3. Value (VAL) and momentum (MOM) long and short side alphas across size quintiles over time. Plotted are the CAPM alphas of the difference between Quintile 5 and Quintile 1 portfolios formed on value and momentum within size quintiles over four subperiods: July 1926 (January 1927 for momentum) to December 1949, January 1950 to December 1969, January 1970 to December 1989, and January 1990 to December 2011. The contributions to profits from the long side (Quintile 5) and short side (Quintile 1) are highlighted on each graph.

Table 4
Size, value, and momentum returns over time, average trading costs, and institutional ownership.

Reported are coefficient estimates and *t*-statistics from time series regressions of size, value, and momentum returns on time trend variables, aggregate trading cost measures, and measures of institutional and hedge fund investment. The dependent variables are the returns to SMB, HML, UMD, small cap HML, large cap HML, small cap UMD, and large cap UMD. The independent variables in Panel A are time variables, in which the first regression uses dummy variables for 20-year intervals over the entire 1926 to 2011 sample period, and the second regression uses a linear time trend as the regressor. Panel B examines the relation between returns and aggregate trading cost measures for the US stock market over time that include the Jones (2002) total trading cost measure, which accounts for effective spreads plus commissions and average turnover on the Dow Jones stocks from 1926 through 2005 averaged each year across all stocks, the Jones (2002) effective spread measure, which is the annual cross-sectional average of effective spreads on the Dow Jones stocks from 1926 to 2005, and the value-weighted average of the Hasbrouck (2009) Gibbs's sampler estimate of effective trading costs across all NYSE stocks each year from 1926 to 2011. Panel C examines the relation between returns and institutional investment proxies that include the percentage of institutional ownership (IO) of corporate equities from the Flow of Funds Account quarterly from 1945 to 2011 and the annual hedge fund assets under management (AUM) from Dow Jones Credit Suisse as a percentage of institutional ownership from 1990 to 2011. Beginning of year values are used for the institutional investment proxies. All variables in Panels B and C are detrended using a linear time trend.

	SMB	HML	UMD	Small value	Large value	Small momentum	Large momentum	Sample period
Panel A: Time trend variables								
1950–1969	−0.240	−0.144	0.425	−0.628	−0.642	1.213	0.833	
	(−0.87)	(−0.47)	(1.07)	(−0.94)	(−1.43)	(2.22)	(1.47)	
1970–1989	−0.171	0.217	0.167	−0.222	−0.192	1.495	0.328	1926–2011
	(−0.62)	(0.71)	(0.42)	(−0.33)	(−0.43)	(2.74)	(0.58)	
1990–2011	−0.138	−0.140	0.011	−0.244	−0.729	1.398	0.215	
	(−0.51)	(−0.47)	(0.03)	(−0.37)	(−1.66)	(2.62)	(0.39)	
Time trend	−0.002	−0.004	−0.029	−0.035	−0.091	0.193	−0.006	1926–2011
	(−0.05)	(−0.08)	(−0.51)	(−0.36)	(−1.39)	(2.44)	(−0.07)	
Panel B: Trading Cost Measures								
Levels								
Average trading cost	−0.680	0.337	1.440	1.697	1.605	2.421	0.098	1926–2005
	(−0.74)	(0.33)	(1.08)	(0.76)	(1.07)	(1.33)	(0.05)	
Effective spread	0.953	0.730	−1.700	−0.819	1.204	−2.008	−1.791	1926–2005
	(2.10)	(1.45)	(−2.57)	(−0.74)	(1.63)	(−2.21)	(−1.90)	
Hasbrouck Gibbs's estimate	1.500	1.156	−3.093	0.705	2.246	−3.048	−5.413	1926–2011
	(2.51)	(1.74)	(−3.59)	(0.48)	(2.31)	(−2.57)	(−4.43)	
First differences								
Average trading cost	0.246	3.306	0.574	9.789	4.025	−3.623	2.714	1927–2005
	(0.13)	(1.63)	(0.22)	(2.21)	(1.36)	(−1.01)	(0.73)	
Effective spread	0.069	0.029	0.469	−1.789	0.536	0.682	0.667	1927–2005
	(0.18)	(0.07)	(0.85)	(−1.93)	(0.89)	(0.91)	(0.85)	
Hasbrouck Gibbs's estimate	−2.107	0.803	−2.847	−4.862	2.406	−1.904	−3.957	1927–2011
	(−2.43)	(0.83)	(−2.28)	(−2.31)	(1.83)	(−1.12)	(−2.23)	
Post−1950								
Levels								
Average trading cost	−0.284	1.423	1.022	1.614	1.736	5.717	−3.015	1950–2005
	(−0.21)	(1.11)	(0.55)	(0.85)	(0.94)	(2.63)	(−1.16)	
Effective spread	0.409	−0.449	0.592	−0.793	−0.104	0.474	1.757	1950–2005
	(0.82)	(−0.93)	(0.84)	(−1.11)	(−0.15)	(0.58)	(1.79)	
Hasbrouck Gibbs's estimate	−1.277	1.048	3.132	1.451	−1.043	8.938	0.047	1950–2011
	(−0.90)	(0.76)	(1.56)	(0.71)	(−0.53)	(3.84)	(0.02)	
First differences								
Average trading cost	5.158	−1.712	−1.356	−6.122	−1.770	−3.553	−0.944	1950–2005
	(1.61)	(−0.56)	(−0.30)	(−1.34)	(−0.40)	(−0.67)	(−0.15)	
Effective spread	0.324	−0.515	2.060	−0.879	−0.248	2.585	2.641	1950–2005
	(0.85)	(−1.42)	(3.84)	(−1.62)	(−0.47)	(4.16)	(3.53)	
Hasbrouck Gibbs's estimate	−2.300	−1.827	7.645	−1.750	−2.549	10.493	8.469	1950–2011
	(−1.45)	(−1.22)	(3.44)	(−0.78)	(−1.17)	(4.08)	(2.73)	
Panel C: Institutional and hedge fund investment								
Levels								
Institutional ownership	−11.275	−3.125	−2.071	1.434	−1.993	−3.739	−3.311	1945–2010
	(−3.25)	(−0.92)	(−0.42)	(0.28)	(−0.41)	(−0.64)	(−0.48)	
Hedge fund AUM/IO	−0.001	−0.001	−0.001	0.001	−0.001	−0.003	−0.001	1990–2010
	(−1.08)	(−1.03)	(−0.91)	(0.32)	(−0.49)	(−1.88)	(−0.06)	
First differences								
Institutional ownership	15.169	6.668	−14.333	13.980	−4.950	−11.912	−19.248	1946–2010
	(2.13)	(0.96)	(−1.42)	(1.35)	(−0.50)	(−1.01)	(−1.36)	
Hedge fund AUM/IO	0.001	−0.001	−0.003	−0.002	0.001	−0.004	−0.003	1991–2010
	(1.09)	(−0.80)	(−1.71)	(−1.24)	(0.45)	(−2.07)	(−1.08)	

premium among large cap stocks in three of the four subperiods. The largest two size quintiles exhibit a significant value premium only in the period from 1970 to 1989. One possible reason for the poor showing of value among large cap stocks in the early part of the century is that book values of equity, which are obtained from Moody's, are estimated less precisely than they are in the latter part of the sample, which comes from Compustat. This explanation, however, does not seem to reconcile why large cap value does not exhibit much of a premium in the 1990 to 2011 period or why value among small caps, which presumably are estimated with more error, does so well prior to 1963. Aside from the 40% largest stocks, there is a robust and relatively stable value premium among the first three size quintiles over time.

Table A3 in the Appendix also shows evidence of a consistently stronger value premium among small cap stocks and a negligible value premium among the largest two size quintiles that is robust across subsamples. Both within the samples used by Hong, Lim, and Stein (2000) and Grinblatt and Moskowitz (2004), as well as outside of those sample periods, a clear interaction exists between size and value, where value returns get weaker as size increases and are nonexistent among the largest two size quintiles. It is also the case that the size-value interaction is mostly driven by the short side. No reliable differences are evident across size quintiles in terms of long-only value returns.

The contribution to value and momentum profits from long and short positions exhibit some variation over time, but not consistently so across size quintiles, and appears to largely be driven by random variation. Across the size quintiles, the only significant pattern we detect is that shorting losers becomes a larger part of momentum profitability as size increases, and this pattern holds in three of the four subperiods, although it is not particularly strong. For value, we also see a time-consistent interaction between the importance of shorting and firm size, wherein every subperiod shorting becomes more important for a value strategy as size decreases, and the returns to value also rise as size declines.

Fig. A1 in the Appendix repeats Fig. 3 for other measures of value within size quintiles: E/P, C/P, D/P, -*Ret*(1,60), and a composite index of these four measures and BE/ME. (E/P and C/P are available beginning in July 1951, D/P in July 1927, –*Ret*(1,60) in July 1931, and BE/ME in July 1926). Results are reported over the full sample period from each measure's start date through December 2011 and over three subperiods: January 1950 to December 1969, January 1970 to December 1989, and January 1990 to December 2011. As Fig. A1 in the Appendix shows, generally a consistent relation exists between size and value across the different value measures, where value premia are stronger among small stocks, although the relation is not as striking as it is for BE/ME (Fig. 3). Moreover, the negative relation between firm size and value premia is also stable over time, where value premia in the smallest quintile of stocks are consistently larger than they are among the largest quintile of stocks for almost every value measure in each of the 20-year subperiods (the exceptions being D/P-sorted portfolios from 1970 to 1989 and 1990 to 2011). However, the relation between size and value premia is not consistently monotonic for the different value measures in the different time periods. In addition, the alpha for value among the largest stocks is still small, but it is no longer negligible when using the other value measures. E/P, C/P, D/P, -*Ret*(1,60), and the composite value measure all produce larger value premia than BE/ME among the largest quintile of stocks that are marginally significant (with *t*-statistics of 2.87, 2.82, 2.47, 2.10, and 2.77, respectively) over the full sample period.

To test for the existence of any time trends more formally, we regress the time series of SMB, HML, and UMD returns on dummy variables for the four 20-year subperiods we use in Fig. 3: 1950 to 1969, 1970 to 1989, and 1990 to 2011, with the omitted period 1926 to 1949 captured by the constant term. Panel A of Table 4 reports the results from these regressions, which indicate no statistical significance for any of the time dummies for any of the strategies. Hence, we fail to reject the hypothesis that size, value, or momentum premia have changed significantly over these subperiods. The next four columns of Panel A of Table 4 report results for the same regressions using only the smallest half and largest half of stocks separately to construct HML (value) and UMD (momentum). Other than small cap momentum being stronger outside of the 1926 to 1949 period, as indicated by the significant and similar-size coefficients on all the other time dummies, no evidence shows that returns for small or large cap value or large cap momentum are any different across any of the four 20-year subperiods, including the most recent period following the discovery of these anomalies and the influx of hedge funds and other investors into these strategies. The last row of Panel A of Table 4 reports results from time series regressions on a linear time trend instead of the 20-year time dummies. Once again, there is no significant time trend in size, value, or momentum returns and no reliable time trend in small and large cap value or large cap momentum. The only significant trend is a positive one for small cap momentum, but this is due entirely to the relatively poor performance of small cap momentum from 1926 to 1949 as shown previously.[12]

The evidence in Table 4, Panel A indicates no significant time trend in size, value, or momentum return premia. Chordia, Subrahmanyam, and Tong (2012) examine a host of anomalies, including size, value, and momentum, and conclude that size and momentum returns have declined significantly over time. Their study examines returns from 1963 to 2010 and compares Fama and MacBeth regression coefficients over time, which can vary by scale from month to month and, hence, can make time series comparisons difficult (e.g., the Fama and MacBeth coefficient, which represents a zero-cost portfolio return, in one period could be scaled by a factor many times higher than the coefficient in another period). We simply compare returns of a constant dollar long-short strategy over the entire 1926 to 2011 time period and find no significant time variation in size, value, or momentum premia.

In an exercise similar in spirit to Schwert (2003), McLean and Pontiff (2012) examine how returns to a

[12] Daniel and Moskowitz (2012) show further that the poor performance of momentum, particularly among small cap stocks, in this period is driven by small losers rebounding abruptly after the Great Depression and link this to their conditional market betas.

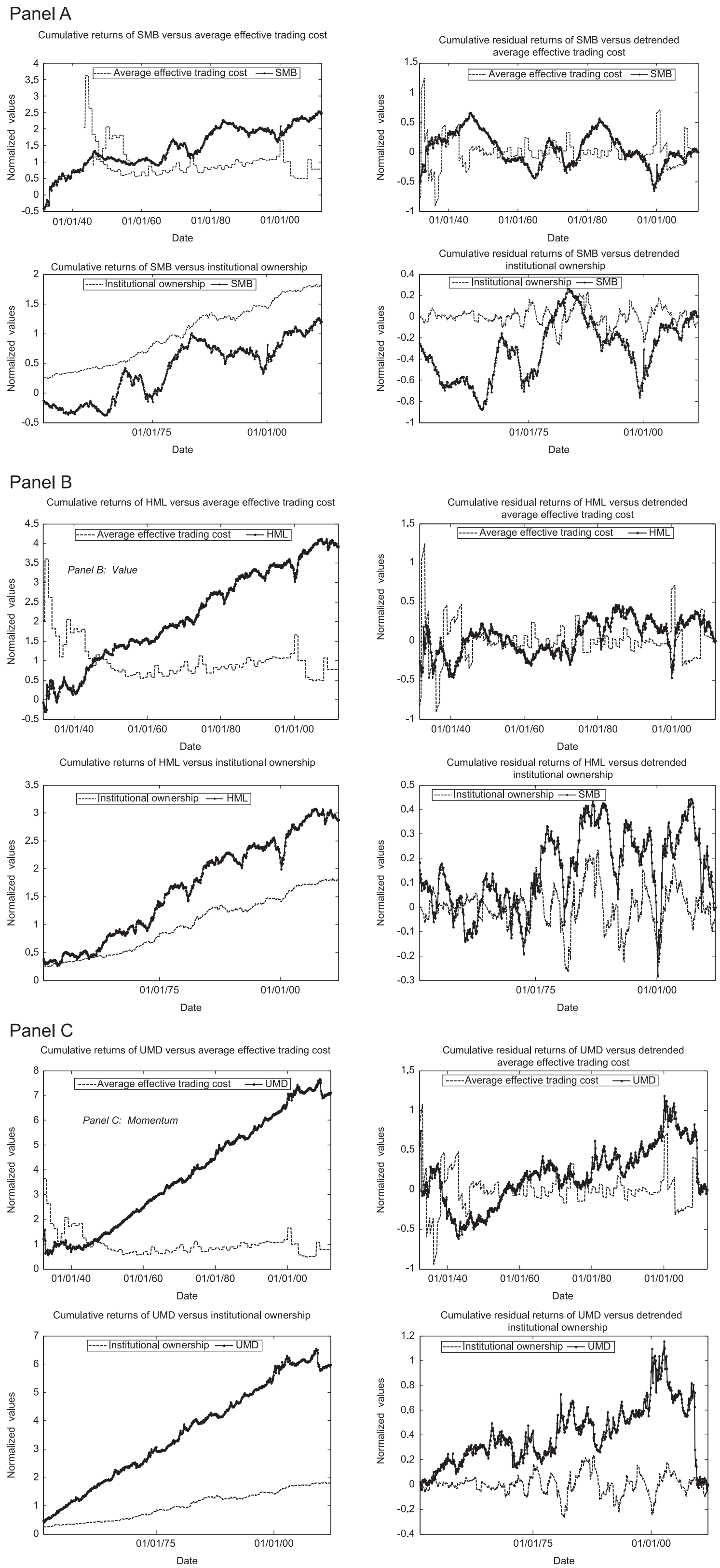

Fig. 4. Size, value, and momentum returns versus average trading costs and institutional ownership over time. The graphs plot the returns to size (Panel A), value (Panel B), and momentum (Panel C) using the Fama and French zero-cost portfolios SMB, HML, and UMD, respectively, against the time series of average effective trading costs from Hasbrouck (2009), which is a value-weighted average across all stocks' effective trading costs measured using the Gibbs's sampler in Hasbrouck annually over the period July 1926 to December 2011, and against the percentage of institutional ownership of corporate equities from the Flow of Funds Account from January 1945 to December 2011. The left-most graphs in each panel plot the cumulative raw returns of each strategy against the time series of effective trading costs and institutional ownership, and the right-most graphs plot the cumulative residual returns of each strategy relative to the market portfolio against the (linear) detrended time series of effective trading costs and institutional ownership. Each series is normalized by a constant to plot the series on the same scale.

variety of anomalies, including size, value, and momentum, vary before and after academic discovery and eventual publication. They find that there is generally some degradation in profits to these strategies after their publication and interpret this result as evidence that arbitrageurs could have competed some of the profits away after their discovery but, in the case of value and momentum, did not eliminate them completely. In Subsection 5.2, this effect is considered more directly by examining time variation in trading costs and institutional and hedge fund investment.

5.2. Trading costs and institutional investment over time

We examine the role arbitrage capital might or might not have played in the variation of profitability to size, value, and momentum strategies over time. Specifically, we look at how profits to these strategies have varied with aggregate trading cost measures, which is likely inversely related to the amount of arbitrage activity, as well as direct measures of institutional and hedge fund investment. The trading cost measures come from Jones (2002) and Hasbrouck (2009), who provide annual estimates of trading costs dating back to 1926. Jones (2002) calculates the average effective spread for the Dow Jones Industrial Average stocks annually from 1926 to 1998 and an estimate of the average annual total trading cost by using the effective spread, average annual turnover, and commission rates for these stocks. He also provided us with updated data through 2005, giving us a time series of aggregate trading costs from 1926 to 2005. Hasbrouck (2009) offers estimates of effective spreads annually for all NYSE-listed firms from 1926 to 2009 using a Gibbs sampler estimate, which we updated through 2011. We compute the value-weighted (and equal-weighted) average of these effective spreads across all NYSE stocks each year from 1926 to 2011 and use that as another proxy for aggregate trading costs over time. The correlation between the Jones (2002) and Hasbrouck (2009) measures of aggregate effective spreads is 0.60 (value-weighted and equal-weighted averages yield similar results). We also use quarterly institutional ownership (as a percentage of total market cap) data from the Flow of Funds Account (FFA) from 1945 to 2011 and total hedge fund assets under management from Dow Jones Credit Suisse annually from 1990 to 2011, as a percentage of total institutional ownership.

Fig. 4 plots the returns to size (Panel A), value (Panel B), and momentum (Panel C) over time with the time series of the Hasbrouck (2009) effective trading cost and institutional ownership from the FFA. Each panel contains four graphs. The top left graph plots the cumulative returns (cumulative sum of log returns) of each strategy with the average effective trading cost and the bottom left graph plots the cumulative returns with institutional ownership. As the left-most graphs in each panel indicate, there is a downward trend in trading costs over time and a pronounced steady upward trend in institutional ownership. Because these trends are driven by many possible omitted factors, examining deviations from these trends is probably more useful. Hence, the upper right and lower right graphs in each panel plot the detrended (using a linear time trend) series of average effective trading costs and institutional ownership, respectively, versus the cumulative residual returns from the market model of each strategy, which in essence detrends the time series of returns from growth in the US equity market as a whole.[13] Looking at the detrended plots on the right hand side of each panel, Panel A of Fig. 4 shows that the residual returns to SMB tend to move with detrended trading costs and move opposite to trend deviations in institutional ownership. For value, in Panel B of Fig. 4, there does not appear to be much of a relation between the residual returns and trend deviations in either trading costs or institutional ownership. For momentum, in Panel C of Fig. 4, the residual returns appear positively related to trading cost trend deviations but unrelated to detrended institutional ownership.

More formally, Table 4, Panel B reports results from time series regressions of SMB, HML, UMD and small and large cap value and momentum strategies on both the levels and changes in average trading costs from Jones (2002), the average effective spread from Jones (2002), and the (value-weighted) average effective spread from Hasbrouck (2009) in six separate regressions. The first three rows present the results from regressions on levels of each of the three trading cost variables, and the next three rows report the coefficients from regressions on first differences of these variables. The signs and significance of the coefficient estimates change depending on whether we examine levels or changes in these variables. For example, in levels, both the Jones (2002) and Hasbrouck (2009) effective cost measures exhibit a positive relation to size returns and negative relation to momentum returns. However, when looking at changes in these variables, the relation to the size premium flips sign. Thus, returns to size are larger when the level of trading costs is high, perhaps consistent with limited arbitrage activity making the size premium larger, but the returns to size strategies are lower when trading costs are rising, which seems inconsistent with this explanation.

Looking at the graphs in Fig. 4, estimated effective spreads near the beginning of the sample period are substantially higher than at other times and are subject to more error because the information used to calculate the spreads was not as easily attainable or reliable at that time. These significant outliers could be influencing the regression results. Hence, the next six rows of Panel B of Table 4 repeat the same time series regressions using only data after 1950, when trading cost estimates become more reliable. Here, we find consistent sign and significance of coefficients whether using levels or changes in the trading cost measures, and we find that most of the significant coefficients from using the full sample of data that includes the early trading cost estimates become insignificant in the post-1950 sample. The aggregate total trading cost measure of Jones (2002), which includes fixed cost commissions, variable cost effective spreads, and turnover, exhibits no relation with the returns of any of these strategies in either levels or first differences. The effective cost spread measures of Jones (2002) and Hasbrouck (2009) are not related to any of the strategies'

[13] Nonlinear filters such as Hodrick and Prescott yield similar results.

returns in levels, and in changes appear to be significantly related only to momentum, particularly small cap momentum. These results suggest that increases in trading costs coincide with momentum strategies becoming more profitable, perhaps because higher trading costs limit arbitrage activity that would otherwise dampen momentum. Because momentum is a much higher turnover strategy than size or value (Israel and Moskowitz, 2012), it makes sense that variable trading costs might impact momentum more so than the other strategies. In addition, the fact that small cap momentum is particularly sensitive to effective trading cost changes is consistent with this conjecture.[14,15]

Panel C of Table 4 reports results from time series regressions of the strategies' returns on beginning of year institutional ownership levels (from 1945 to 2010) and changes (from 1946 to 2010) as well as hedge fund assets under management divided by institutional ownership in both levels (from 1990 to 2010) and changes (from 1991 to 2010). Aside from SMB, which has a negative relation with the level of institutional ownership and a positive relation with changes in institutional ownership, consistent with Gompers and Metrick (2001), no significant relation exists between trading strategy profits and institutional ownership levels or changes. For hedge fund assets, the only marginally significant result is that small cap momentum appears to do worse when either the level of hedge fund assets is high or hedge fund assets are increasing. This result is also consistent with arbitrage activity, as proxied by hedge fund investment, lowering the profits to momentum trading strategies, particularly in small stocks, and is consistent with the results obtained from effective trading costs above.

6. International and other asset class evidence

For further robustness on the importance of shorting, we also examine the value and momentum portfolios of Asness, Moskowitz, and Pedersen (forthcoming) in international equity markets and other asset classes. The data span the January 1972 to December 2011 time period, with some variation in starting dates for some markets and asset classes. Here, we examine neither time variation in the returns to value and momentum because of the short sample period nor the role of firm size because size is not an easily applied characteristic in some asset classes (e.g., currencies or commodities).

Table 5 reports the alphas (over the local market index) of return differences between the top and bottom third of value and momentum-sorted portfolios from Asness, Moskowitz, and Pedersen (forthcoming) as described in Section 2. Alphas are calculated relative to the relevant MSCI index for each local market for the individual stock strategies in the US, UK, Europe, and Japan and are calculated relative to an equal-weighted average of all securities in each asset class for the other asset classes. The t-statistics of the alphas, the alpha of the long side only (Portfolio 3) and its t-statistic, and the percentage of high minus low total profits coming from the long side are reported. We also report the t-statistic for whether the long side and short side contribution to profits are significantly different from each other. Panel A of Table 5 reports results for the individual stock strategies globally, and Panel B of Table 5 reports results for the other asset classes.

Beginning with the international stock data in Panel A of Table 5, we see that value and momentum premia are robust across international equity markets. These results are identical to those in Asness, Moskowitz, and Pedersen (forthcoming) and consistent with those in Fama and French (2012). The only exceptions seem to be the lack of a value premium in the UK and Europe and the lack of a momentum premium in Japan. All exhibit positive profits, but are statistically insignificant.[16] The lack of significance of value in the UK and Europe and lack of a momentum premium in Japan are perfectly consistent with random chance.[17] Long-only value portfolios exhibit positive and significant alphas in every region and long-only momentum portfolios produce positive alphas in every region that are also statistically significant, except for Japan.

We also report results for global average portfolios, in which we weight each market by the inverse of its full sample volatility (standard deviation of returns) such that each market contributes an equal amount to total ex post volatility because return volatility varies widely across asset classes. (For example, the volatility of commodities and equities is about seven times that of fixed income instruments and about five times that of currencies.) The global portfolios exhibit strong value and momentum effects in both long-short and long-only contexts.

Examining the percentage of value and momentum profits that come from the long side, we find that slightly more than half of the value and momentum profits come from the long side (on average 59.4% for value and 59.2% for momentum). Statistically, we cannot reject that value profits are split evenly between the long and short sides, and we cannot reject that the long and short sides of momentum contribute equally to profits. Hence, a 50–50 contribution from long and short positions seems to accurately reflect the composition of both value and momentum profits across all markets. This is consistent with our earlier results for US stock portfolios over a longer time period.

Panel B of Table 5 shows consistent value and momentum premia across diverse asset classes for both long-short and long-only portfolios. Consistent with our

[14] Lagging the trading cost measures produces similar results as well.

[15] See Frazzini, Israel and Moskowitz (2012) for a detailed discussion of the trading costs of asset pricing anomalies, including those examined in this paper.

[16] Fama and French (2012) do find a robust value premium in the UK and Europe among smaller stocks. Because the Asness, Moskowitz, and Pedersen (forthcoming) portfolios use primarily large-cap stocks and are value weighted, the value premium is weaker.

[17] Asness (2011) argues that evidence exists of momentum in Japan when evaluating momentum relative to a value strategy. As Asness (2011) and Asness, Moskowitz, and Pedersen, (forthcoming) argue the strong negative correlation between value and momentum and strong performance of value in Japan makes momentum returns in Japan look weak when viewed on a stand-alone basis. The same argument can be made to explain the apparent poor showing of value in the UK or Europe over this period, when momentum was strong.

Table 5

Profitability from long and short side of value and momentum portfolios across markets and asset classes.

Reported are the alphas (over the local market index) of return differences between the top and bottom third of value and momentum-sorted portfolios from Asness, Moskowitz, and Pedersen (forthcoming) across international stock markets and asset classes. Results are reported for individual stock strategies from four regions: the US, UK, Europe (excluding UK), and Japan; and from 18 country equity indexes, government bond futures from ten developed countries, ten currency forwards from ten developed countries relative to the US dollar, and 27 commodity futures. The details of each series are contained in Asness, Moskowitz, and Pedersen, (forthcoming) and all returns are expressed in US dollars. Alphas are calculated relative to the relevant MSCI index for each local market for the individual stock strategies and relative to an equal-weighted average of all contracts for the other asset classes. The *t*-statistics of the alphas, the alpha of the long side only (tretile 3) and its *t*-statistic, as well as the percentage of 3-1 profits coming from the long side and a *t*-statistic for whether the long side and short side contribution to profits is significantly different are reported. Panel A reports results for the individual stock strategies; Panel B, for the other asset classes. Also reported are results for global average portfolios, which are portfolios formed across markets and assets classes, in which each market and asset class is weighted by the inverse of its full sample volatility (standard deviation of returns).

Panel A: International stocks

	US February 1972–December 2011	UK February 1972–December 2011	Europe February 1974–December 2011	Japan February 1974–December 2011	Global stocks February 1974–December 2011
Value					
Alpha of 3-1 spread	5.33	3.74	3.41	12.78	5.76
(*t*-statistic)	(2.66)	(1.58)	(1.70)	(4.78)	(3.49)
Alpha of long side	3.62	3.22	2.84	5.64	3.42
(*t*-statistic)	(3.17)	(2.03)	(2.27)	(2.99)	(3.58)
Percentage long side	68.0	86.1	83.4	44.1	59.4
Long = short (*t*-statistic)	(2.01)	(1.60)	(1.36)	(−0.62)	(1.12)
Momentum					
Alpha of 3-1 spread	5.99	6.77	9.47	1.65	6.00
(*t*-statistic)	(2.30)	(2.68)	(3.97)	(0.54)	(3.05)
Alpha of long side	3.69	3.60	5.91	0.65	3.55
(*t*-statistic)	(2.34)	(2.36)	(4.12)	(0.38)	(3.13)
Percentage long side	61.5	53.1	62.4	39.3	59.2
Long = short (*t*-statistic)	(0.99)	(0.18)	(0.59)	(−0.40)	(1.14)

Panel B: Other asset classes

	Equity indexes January 1978–December 2011	Currencies January 1979–December 2011	Fixed income January 1982–December 2011	Commodities January 1972–December 2011	Global other January 1982–December 2011	Global all assets January 1982–December 2011
Value						
Alpha of 3-1 spread	5.96	3.32	1.77	7.80	3.28	4.61
(*t*-statistic)	(3.45)	(1.81)	(1.68)	(2.02)	(3.29)	(4.33)
Alpha of long side	2.72	2.01	0.60	4.83	1.61	2.53
(*t*-statistic)	(2.76)	(2.01)	(1.03)	(2.34)	(2.99)	(4.24)
Percentage long side	45.6	60.5	34.0	61.9	49.0	55.0
Long = short (*t*-statistic)	(−0.54)	(1.01)	(−0.95)	(1.14)	(−0.16)	(0.91)
Momentum						
Alpha of 3-1 spread	8.37	3.49	−0.29	11.51	3.51	4.67
(*t*-statistic)	(4.00)	(1.83)	(−0.29)	(3.06)	(3.14)	(3.08)
Alpha of long side	4.43	2.02	−0.10	5.89	1.89	2.50
(*t*-statistic)	(4.00)	(2.02)	(−0.17)	(2.71)	(3.15)	(2.97)
Percentage long side	53.0	58.0	34.0	51.2	53.9	53.7
Long = short (*t*-statistic)	(0.57)	(0.83)	(−0.17)	(0.17)	(0.67)	(0.53)

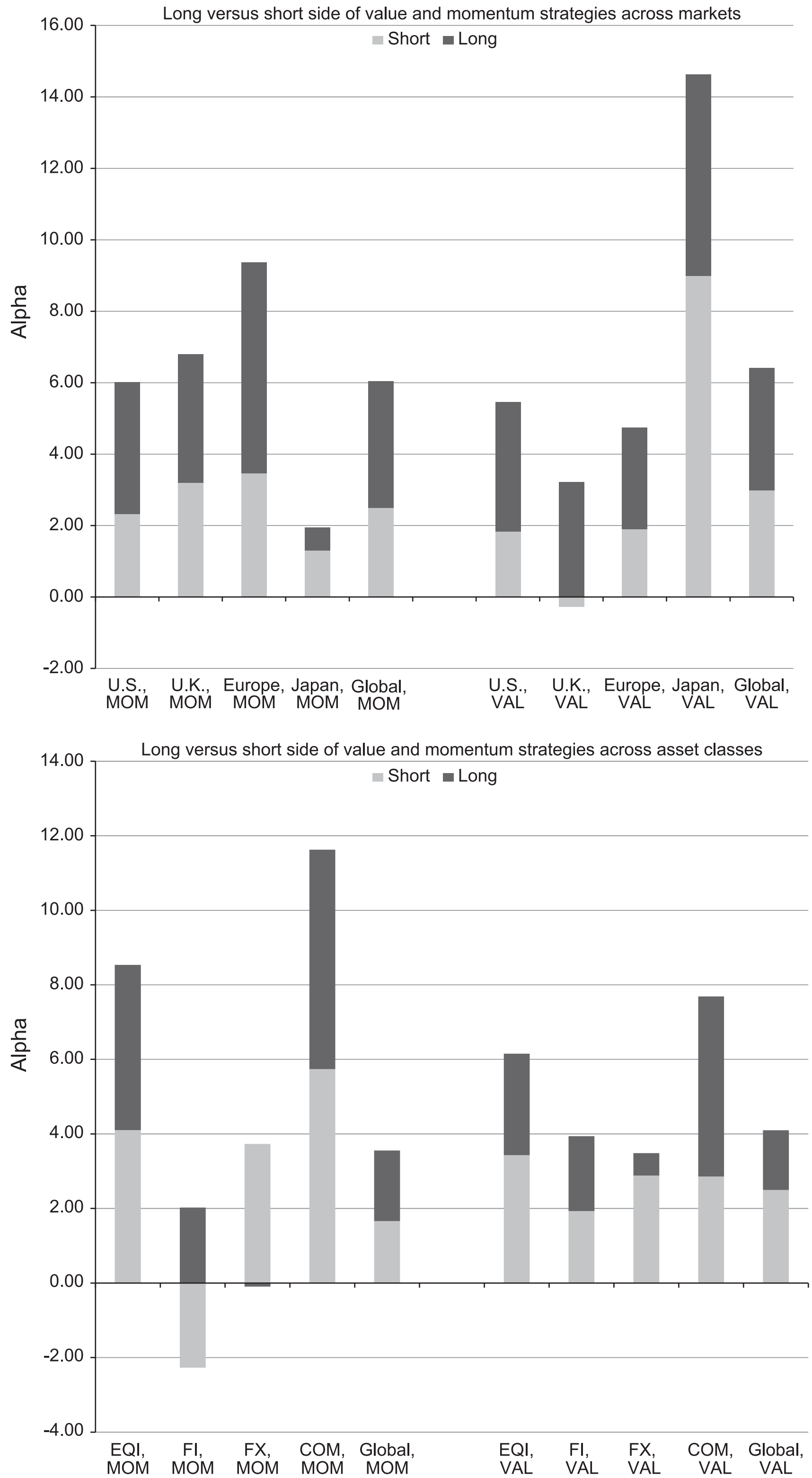

Fig. 5. Long and short side contributions to value (VAL) and momentum (MOM) profitability across markets and asset classes. Plotted are the local market alphas of the difference between the top and bottom third value-weighted portfolios formed on value and momentum across international markets and asset classes. The contribution from the long side (top third) versus the short side (bottom third) is highlighted on the graph. The top graph shows results across four international stock regions: US, UK, Europe, and Japan. The bottom graph shows results across four asset classes: equity indexes (EQI), fixed income (FI), currencies (FX), and commodities (COM). Also reported are global averages across the regions and across asset classes, in which each region or asset class is weighted by the inverse of its full sample volatility.

previous results, we find that the contribution from the long side for value is 49%, and the contribution from the long side for momentum is about 54%. Overall, across all markets and asset classes, the contribution to profits comes equally from the long and short sides for both value and momentum. Fig. 5 summarizes these findings by plotting the alphas of value and momentum portfolios across markets and asset classes, highlighting the contribution from the long and short sides.

7. Conclusion

We examine the role of shorting, firm size, and time on size, value, and momentum strategies over the last century in US data and over the last four decades in international stock markets and other nonstock asset classes. We find that the returns to value decrease with size over our sample period and are insignificant for the largest stocks. Momentum premia are present in every size group and do not vary reliably across size groups over the entire sample period. We find no consistent evidence that momentum returns decrease with firm size as suggested by the literature. We also find that about half of value profits and half of momentum profits come from the long side. We find no evidence that shorting profits are more important for momentum, in contrast to claims in the literature. The role of shorting and size on momentum profits previously shown in the literature are not a robust feature of the data. Using a much longer time series and looking across other equity markets and asset classes, we find no reliable size effect in momentum or stronger role for shorting. However, the contribution of long versus short positions does vary with firm size. Short selling profits become more important for momentum strategies and less important for value strategies as size increases, and they become less important for momentum and more important for value as size decreases. These patterns are generally consistent over time. Long-only versions of value and momentum also consistently yield positive alphas across size groups, across markets and asset classes, and across time. Overall, the premium for momentum, whether long-short or long-only, appears to be consistently higher than that of value, especially among large cap stocks in which the value premium is weakest.

Finally, we examine whether profits to these strategies have changed significantly over time or in relation to changes in trading costs or institutional and hedge fund investment over time. We find little evidence that size, value, or momentum premia have changed over time or are affected by changes in institutional or hedge fund participation in markets and find only mild evidence that trading costs have any relation to the profitability of these strategies. Our results have implications for understanding the nature of size, value, and momentum return premia and for implementing size, value, and momentum portfolios in practice.

Appendix A

See Fig. A1 and Tables A1–A4.

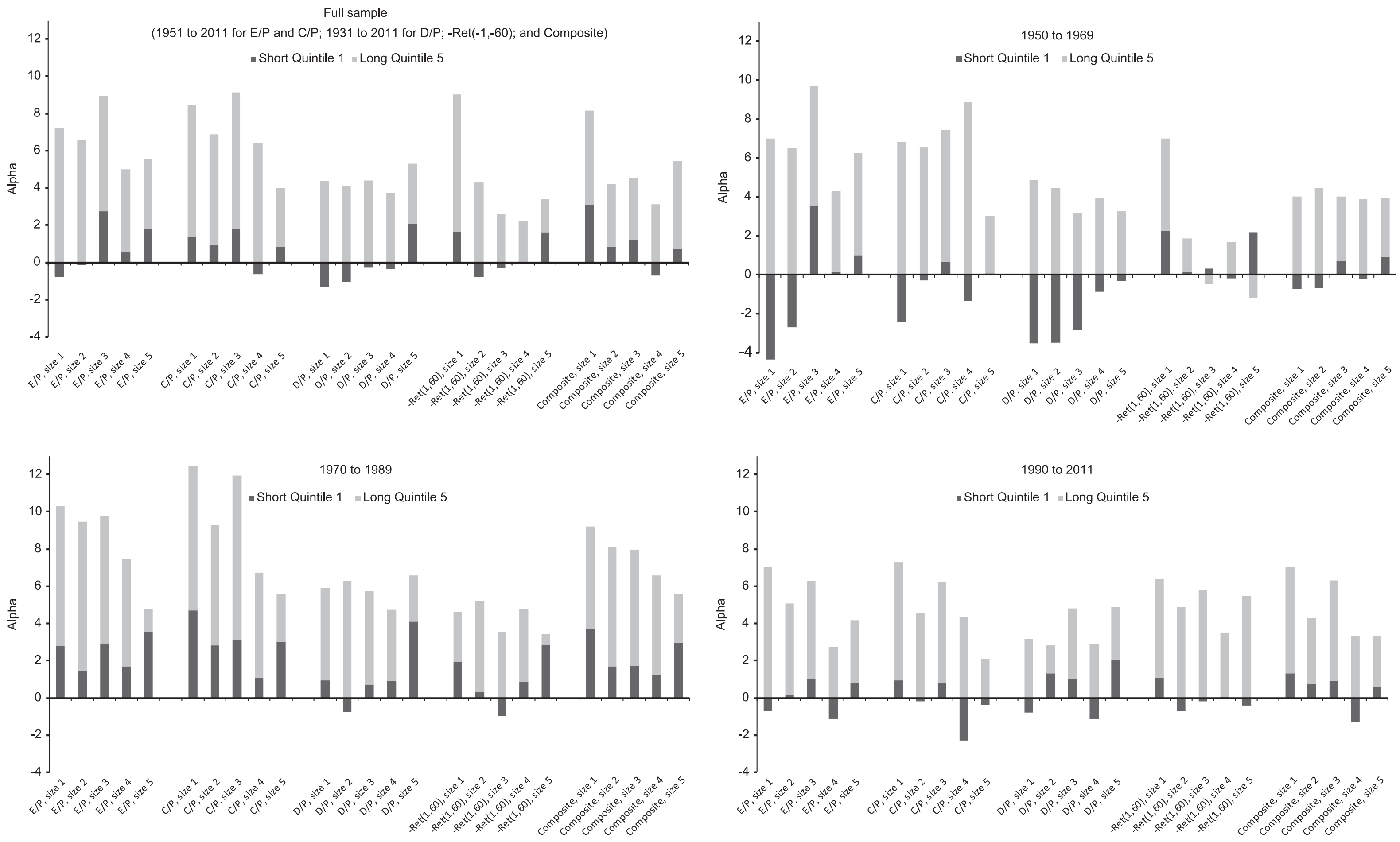

Fig. A1. Other value measures' long and short side alphas across size quintiles over time. Plotted are the CAPM alphas of the difference between Quintile 5 and Quintile 1 portfolios formed on five other measures of value within size quintiles. The measures of value are: E/P, C/P, D/P, and [-*Ret*(1,60)], where the E/P and C/P portfolios begin in July 1951, the D/P portfolios begin in July 1927, and the –*Ret*(1,60) portfolios begin in July 1931. Results are reported over the full sample period from each measure's start date to December 2011 and over three subperiods: January 1950 to December 1969, January 1970 to December 1989, and January 1990 to December 2011. The contributions to profits from the long side (Quintile 5) and short side (Quintile 1) are highlighted on each graph.

Table A1
Decile portfolios formed from other measures of value.

Reported are the average raw returns in excess of the one-month T-bill rate, Sharpe ratios, and CAPM alphas and *t*-statistics of value-weighted decile portfolios formed on other measures of value: E/P, C/P, D/P, BE/ME and [-*Ret*(1,60)]. The difference between Deciles 10 and 1 (10-1) is also reported along with the differences between the average of Deciles 9 and 10 and the average of Deciles 1 and 2 (9-2), the average of Deciles 8 through 10 and the average of Deciles 1 through 3 (8-3), and the average of Deciles 7 through 10 and the average of Deciles 1 through 4 (7-4). The E/P and C/P portfolios begin in July 1951, the D/P portfolios begin in July 1927, and the –*Ret*(1,60) portfolios begin in July 1931. All series end in December 2011. Also reported are results for the D/P and –*Ret*(1,60) portfolios over the common period 1951 to 2011, as well as BE/ME-sorted portfolios over the same period for comparison. Finally, results from Decile portfolios from a composite index of value measures, which is the equal-weighted average of all five value measures [BE/ME, E/P, C/P, D/P, and -*Ret*(1,60)] are also reported from 1926 to 2011, using all available value measures at each point in time.

	Decile portfolios (value-weighted)										Differences			
	1	2	3	4	5	6	7	8	9	10	10-1	9-2	8-3	7-4
E/P, 1951–2011														
Raw excess	5.59	5.12	6.62	6.33	7.13	9.01	9.37	10.17	11.14	12.08	6.48	6.25	5.35	4.77
Sharpe	0.29	0.32	0.43	0.43	0.47	0.60	0.63	0.65	0.67	0.67	0.45	0.55	0.57	0.60
Alpha	−2.12	−1.50	0.42	0.34	0.96	3.08	3.50	4.16	4.83	5.21	7.33	6.83	5.80	5.14
t-statistics	(−2.12)	(−2.17)	(0.55)	(0.45)	(1.28)	(3.57)	(4.13)	(4.19)	(4.49)	(4.43)	(4.00)	(4.70)	(4.76)	(4.99)
C/P, 1951–2011														
Raw excess	5.49	6.08	5.69	7.18	7.66	7.45	8.18	9.04	10.47	12.15	6.67	5.53	4.80	3.85
Sharpe	0.29	0.38	0.37	0.46	0.49	0.48	0.55	0.59	0.67	0.67	0.47	0.49	0.50	0.48
Alpha	−2.12	−0.50	−0.55	0.89	1.39	1.43	2.44	3.20	4.52	5.38	7.50	6.26	5.42	4.45
t-statistics	(−2.31)	(−0.70)	(−0.73)	(1.20)	(1.73)	(1.61)	(2.71)	(3.27)	(4.52)	(4.51)	(4.14)	(4.31)	(4.44)	(4.36)
D/P, 1927–2011														
Raw excess	6.59	7.61	6.94	8.29	6.70	7.96	9.00	9.50	9.32	8.73	2.14	1.92	2.13	1.78
Sharpe	0.29	0.38	0.36	0.44	0.34	0.41	0.47	0.47	0.44	0.38	0.11	0.13	0.16	0.17
Alpha	−1.44	0.31	−0.05	1.48	−0.34	1.19	2.30	2.56	2.23	1.47	2.91	2.41	2.48	2.06
t-statistics	(−1.61)	(0.43)	(−0.07)	(2.17)	(−0.42)	(1.41)	(2.79)	(2.61)	(1.99)	(0.99)	(1.43)	(1.45)	(1.73)	(1.76)
-*Ret*(−1,−60), 1931–2011														
Raw excess	7.05	6.90	8.65	8.78	8.42	9.54	8.98	11.30	11.18	13.55	6.50	5.39	4.48	3.41
Sharpe	0.32	0.34	0.44	0.43	0.43	0.44	0.42	0.47	0.41	0.44	0.29	0.29	0.28	0.26
Alpha	−1.37	−0.81	1.02	0.98	0.87	1.40	0.98	2.50	1.48	3.29	4.65	3.48	2.81	2.11
t-statistics	(−1.46)	(−1.13)	(1.47)	(1.29)	(1.14)	(1.59)	(1.07)	(2.15)	(1.02)	(1.68)	(1.90)	(1.72)	(1.64)	(1.47)
D/P, 1951–2011														
Raw excess	6.59	7.61	6.94	8.29	6.70	7.96	9.00	9.50	9.32	8.73	2.14	1.92	2.13	1.78
Sharpe	0.29	0.38	0.36	0.44	0.34	0.41	0.47	0.47	0.44	0.38	0.11	0.13	0.16	0.17
Alpha	−1.37	−0.91	−0.04	1.22	0.10	1.69	1.75	3.69	3.56	2.81	4.18	4.33	4.13	3.23
t-statistics	(−1.44)	(−1.19)	(−0.05)	(1.50)	(0.11)	(1.86)	(1.98)	(3.81)	(3.23)	(1.88)	(2.05)	(2.65)	(3.02)	(2.85)
-*Ret*(−1,−60), 1951–2011														
Raw excess	7.05	6.90	8.65	8.78	8.42	9.54	8.98	11.30	11.18	13.55	6.50	5.39	4.48	3.41
Sharpe	0.32	0.34	0.44	0.43	0.43	0.44	0.42	0.47	0.41	0.44	0.29	0.29	0.28	0.26
Alpha	−1.48	−0.47	0.97	1.79	1.85	1.95	1.57	2.59	1.95	1.91	3.39	2.90	2.47	1.80
t-statistics	(−1.57)	(−0.60)	(1.27)	(2.36)	(2.41)	(2.48)	(1.92)	(2.66)	(1.79)	(1.16)	(1.58)	(1.72)	(1.71)	(1.45)
BE/ME,1951–2011														
Raw excess	6.65	7.68	7.85	7.58	8.38	8.88	9.00	10.83	11.66	12.54	5.89	4.93	4.28	3.57
Sharpe	0.33	0.40	0.42	0.36	0.43	0.41	0.39	0.45	0.44	0.39	0.26	0.28	0.28	0.28
Alpha	−1.32	−0.11	0.69	0.47	1.84	1.76	2.02	3.42	3.66	3.66	4.99	4.38	3.83	3.26
t-statistics	(−1.60)	(−0.18)	(1.06)	(0.63)	(2.32)	(2.29)	(2.22)	(3.44)	(3.48)	(2.51)	(2.51)	(2.95)	(3.09)	(3.13)
Composite, 1926–2011														
Raw excess	6.55	7.18	7.81	7.96	7.72	8.77	9.31	10.49	11.01	12.25	5.70	4.76	4.07	3.39
Sharpe	0.31	0.37	0.42	0.41	0.40	0.44	0.46	0.48	0.46	0.45	0.34	0.34	0.34	0.34
Alpha	−1.34	−0.15	0.70	0.56	0.47	1.23	1.71	2.50	2.41	2.87	4.21	3.38	2.86	2.43
t-statistics	(−2.00)	(−0.32)	(1.46)	(1.09)	(0.87)	(1.92)	(2.58)	(2.87)	(2.39)	(2.11)	(2.35)	(2.30)	(2.24)	(2.31)

Table A2
Analyzing the size effect shown in Banz (1981).

Panel A reports the average raw returns in excess of the one-month T-bill rate, Sharpe ratios, and CAPM alphas of value-weighted and equal-weighted decile portfolio spread returns formed on size over the full sample period from July 1926 to December 2011 and over the original Banz (1981) sample period from January 1936 to December 1975. The difference in returns between Deciles 1 and 10 (1-10) is reported. Panel B reports Fama and MacBeth (1973) cross-sectional regression coefficients, in which the cross section of returns on 25 size and BE/ME and one hundred size and BE/ME sorted portfolios are regressed each month on their market betas (β) and the log of their average market capitalization [log(Size)]. The time series average of the coefficient estimates and the time series *t*-statistics of those coefficients are reported over the full sample period July 1926 to December 2011 and the original Banz (1981) sample period from January 1936 to December 1975. Betas are estimated over each full subsample.

Panel A: Size decile spread portfolio returns		
	Value weighted decile portfolio 1-10 spread	
	1926–2011	**1936–1975** [Banz (1981) sample]
Raw excess	6.86	7.12
Sharpe	0.26	0.29
Alpha	3.03	2.30
	(1.14)	(0.63)
	Equal weighted decile portfolio 1-10 spread	
	1926–2011	**1936–1975** [Banz (1981) sample]
Raw excess	11.81	11.30
Sharpe	0.41	0.41
Alpha	8.38	6.84
	(2.81)	(1.62)
Panel B: Fama and MacBeth coefficients		
	25 Size-BE/ME portfolios	
	1926–2011	**1936–1975** [Banz (1981) sample]
β	−0.204	−0.086
	(−0.57)	(−0.29)
log(Size)	−0.076	−0.068
	(−2.38)	(−2.14)
	100 Size-BE/ME portfolios	
	1926–2011	**1936–1975** [Banz (1981) sample]
β	0.123	0.185
	(0.37)	(0.70)
log(Size)	−0.067	−0.059
	(−2.06)	(−1.72)

Table A3

Profitability of long and short side of value and momentum portfolios across size over sample periods from Hong, Lim, and Stein (2000), Grinblatt and Moskowitz (2004), and excluding those sample periods.

Reported are the CAPM alphas of return differences between Quintiles 5 and 1 of value and momentum sorted portfolios within size quintiles. The t-statistics of the return differences, the returns of the long side only (Quintile 5) and its t-statistic, as well as the percentage of 5-1 profits coming from the long side and a t-statistic for whether the long side and short side contribution to profits is significantly different are also reported. The differences between size Quintiles 1 (smallest) and 5 (largest) are also reported. Results pertain to value-weighted portfolios over five sample periods: January 1980 to December 1996 (pertaining to Hong, Lim, and Stein, 2000), July 1963 to December 1999 (pertaining to Grinblatt and Moskowitz, 2004), July 1963 to December 1999 excluding January 1980 to December 1996, January 1927 to December 2011 excluding January 1980 to December 1996, and January 2000 to December 2011.

	Momentum						Value					
	Smallest				Largest		Smallest				Largest	
	Size 1	Size 2	Size 3	Size 4	Size 5	Size 1-Size 5	Size 1	Size 2	Size 3	Size 4	Size 5	Size 1-Size 5
1980–1996, Hong, Lim, and Stein (2000)												
Alpha of 5-1 spread	22.42	17.09	12.01	7.00	2.28	20.13	17.76	10.72	8.18	5.29	4.34	13.42
(t-statistic)	(8.95)	(5.77)	(3.62)	(1.75)	(0.50)	(5.54)	(7.24)	(3.81)	(2.84)	(1.88)	(1.44)	(4.44)
Alpha of long side	6.31	5.46	5.53	3.54	1.85	4.46	4.81	3.78	4.93	4.34	4.65	0.16
(t-statistic)	(2.28)	(2.29)	(2.47)	(1.81)	(0.94)	(1.38)	(1.91)	(1.75)	(2.56)	(2.33)	(2.14)	(0.05)
Percent long side	28.14	31.97	45.99	50.64	80.82		27.08	35.26	60.21	82.18	107.18	
Long=short (t-statistic)	(1.77)	(1.45)	(0.26)	(0.03)	(0.55)		(1.58)	(0.83)	(0.57)	(1.65)	(2.29)	
1963–1999, Grinblatt and Moskowitz (2004)												
Alpha of 5-1 spread	19.92	17.21	14.58	12.50	9.21	10.71	11.92	9.17	7.93	5.24	2.69	9.23
(t-statistic)	(9.68)	(7.83)	(5.94)	(4.76)	(3.11)	(4.36)	(6.51)	(4.48)	(3.99)	(2.54)	(1.23)	(4.04)
Alpha of long side	9.09	7.43	7.79	6.54	4.03	5.05	6.48	5.28	5.11	4.00	2.66	3.82
(t-statistic)	(4.15)	(4.09)	(4.75)	(4.69)	(2.89)	(2.05)	(3.05)	(2.94)	(3.13)	(2.55)	(1.70)	(1.65)
Percent long side	45.61	43.18	53.44	52.32	43.78		54.36	57.54	64.51	76.27	98.68	
Long=short (t-statistic)	(0.39)	(0.70)	(0.36)	(0.27)	(0.70)		(0.24)	(0.44)	(0.91)	(1.49)	(1.78)	
1963–1999, (excluding 1980–1996)												
Alpha of 5-1 spread	17.66	17.06	16.28	16.85	14.53	3.13	7.08	7.97	7.81	5.41	1.40	5.69
(t-statistic)	(5.62)	(5.36)	(4.66)	(4.88)	(3.87)	(0.97)	(2.69)	(2.71)	(2.84)	(1.82)	(0.45)	(1.70)
Alpha of long side	11.67	9.22	9.64	9.06	5.72	5.96	8.29	6.79	5.52	3.96	1.03	7.26
(t-statistic)	(3.56)	(3.45)	(4.07)	(4.61)	(2.92)	(1.66)	(2.57)	(2.49)	(2.19)	(1.66)	(0.46)	(2.15)
Percent long side	66.09	54.01	59.19	53.75	39.36		117.03	85.23	70.71	73.24	73.79	
Long=short (t-statistic)	(0.86)	(0.28)	(0.74)	(0.42)	(1.50)		(1.47)	(1.17)	(0.83)	(0.87)	(0.33)	
1927–2011, (excluding 1980–1996)												
Alpha of 5-1 spread	10.37	14.40	14.40	15.29	11.60	−1.25	11.97	5.87	4.28	1.32	2.04	9.61
(t-statistic)	(3.66)	(6.13)	(5.39)	(5.32)	(4.21)	(−0.49)	(3.39)	(2.70)	(2.02)	(0.55)	(0.91)	(2.37)
Alpha of long side	10.18	8.49	7.51	7.91	4.23	5.95	7.01	4.66	3.34	1.64	1.62	5.49
(t-statistic)	(4.07)	(4.65)	(5.07)	(5.89)	(3.62)	(2.24)	(2.65)	(2.24)	(1.78)	(0.83)	(0.84)	(2.10)
Percent long side	98.14	58.96	52.13	51.72	36.48		58.57	79.34	77.97	124.18	79.64	
Long=short (t-statistic)	(2.05)	(0.76)	(0.26)	(0.27)	(2.01)		(0.37)	(1.01)	(0.96)	(1.01)	(0.67)	
2000–2011												
Alpha of 5-1 spread	13.12	15.30	14.48	14.19	10.24	2.88	12.99	6.38	4.63	1.54	2.19	10.58
(t-statistic)	(5.59)	(7.66)	(6.32)	(5.72)	(4.23)	(1.31)	(4.52)	(3.41)	(2.53)	(0.74)	(1.14)	(3.21)
Alpha of long side	9.30	7.89	7.26	7.17	3.92	5.37	6.15	4.15	3.26	1.73	1.97	4.31
(t-statistic)	(4.47)	(5.13)	(5.71)	(6.24)	(3.83)	(2.40)	(2.78)	(2.38)	(2.05)	(1.04)	(1.21)	(1.97)
Percent long side	70.87	51.58	50.11	50.54	38.30		47.39	65.09	70.38	112.88	89.92	
Long=short (t-statistic)	(1.34)	(0.17)	(0.02)	(0.09)	(1.78)		(0.15)	(0.67)	(0.89)	(1.18)	(1.15)	

Table A4
Profitability of long and short side of value and momentum portfolios for NYSE only and Nasdaq and Amex only stocks.
Reported are the CAPM alphas of return differences between Quintiles 5 and 1 of value and momentum sorted portfolios across size quintiles for NYSE only and Nasdaq and Amex only stocks. Size breakpoints are based on NYSE stocks only for both the NYSE-only and Nasdaq and Amex only subsamples, so that the same breakpoints are used for each. The *t*-statistics of the return differences, the returns of the long side only (Quintile 5) and its *t*-statistic, as well as the percentage of 5-1 profits coming from the long side and a *t*-statistic for whether the long side and short side contribution to profits is significantly different are also reported. The differences between size Quintiles 1 (smallest) and 5 (largest) are also reported. Results pertain to value-weighted portfolios for NYSE stocks only from January 1927 to December 2011, for NYSE stocks only from July 1963 to December 2011, and for Nasdaq and Amex stocks only from July 1963 to December 2011.

	Smallest				Largest		Smallest				Largest	
	Size 1	Size 2	Size 3	Size 4	Size 5	Size 1-Size 5	Size 1	Size 2	Size 3	Size 4	Size 5	Size 1-Size 5
	Momentum						Value					
1927–2011, NYSE only												
Alpha of 5-1 spread	13.09	13.28	12.21	10.94	9.41	3.69	8.11	3.25	2.81	2.18	3.92	4.18
(*t*-statistic)	(5.31)	(6.63)	(5.75)	(4.94)	(4.08)	(1.47)	(2.62)	(1.82)	(1.72)	(1.13)	(2.03)	(1.15)
Alpha of long side	10.95	7.22	7.04	5.99	4.38	6.57	6.14	3.88	2.88	3.15	4.04	2.10
(*t*-statistic)	(5.20)	(4.91)	(5.91)	(5.63)	(4.54)	(2.85)	(2.74)	(2.27)	(1.83)	(1.91)	(2.40)	(0.93)
Percent long side	83.60	54.38	57.66	54.72	46.52		75.78	119.54	102.58	144.48	102.94	
Long=short (*t*-statistic)	(2.36)	(0.64)	(1.26)	(0.94)	(−0.37)		(0.80)	(1.57)	(1.35)	(2.36)	(2.47)	
1963–2011, NYSE only												
Alpha of 5-1 spread	15.01	13.76	11.13	9.20	9.45	5.56	3.90	2.78	4.55	2.62	2.10	1.80
(*t*-statistic)	(5.60)	(5.54)	(4.41)	(3.63)	(3.37)	(2.05)	(1.52)	(1.51)	(2.55)	(1.37)	(1.12)	(0.62)
Alpha of long side	9.83	7.86	7.44	5.48	4.38	5.44	4.49	4.33	4.31	3.66	1.79	2.70
(*t*-statistic)	(5.00)	(4.71)	(5.05)	(4.19)	(3.47)	(2.41)	(2.14)	(2.60)	(2.54)	(2.34)	(1.17)	(1.24)
Percent long side	65.47	57.13	66.86	59.60	46.37		115.22	155.78	94.83	139.48	85.36	
Long=short (*t*-statistic)	(2.31)	(0.67)	(1.21)	(0.95)	(−0.34)		(0.87)	(1.61)	(1.32)	(2.46)	(2.53)	
1963–2011, Nasdaq/Amex only												
Alpha of 5-1 spread	15.85	16.56	15.52	16.23	16.18	−0.34	12.44	7.28	10.65	10.82	−2.05	14.49
(*t*-statistic)	(5.97)	(5.70)	(4.80)	(4.34)	(3.50)	(−0.08)	(6.34)	(2.82)	(3.35)	(2.92)	(−0.48)	(3.54)
Alpha of long side	9.07	8.19	6.37	6.85	7.77	1.30	7.93	5.19	7.52	8.90	−1.23	9.17
(*t*-statistic)	(4.21)	(3.88)	(2.90)	(3.02)	(2.62)	(0.41)	(4.15)	(2.63)	(3.20)	(2.96)	(−0.36)	(2.54)
Percent long side	57.24	49.45	41.05	42.21	47.99		63.79	71.33	70.60	82.21	60.17	
Long=short (*t*-statistic)	(0.69)	(−0.16)	(−0.50)	(−0.43)	(−0.00)		(0.99)	(1.20)	(1.67)	(2.24)	(0.01)	

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