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Value and Momentum Everywhere

CLIFFORD S. ASNESS, TOBIAS J. MOSKOWITZ, and LASSE HEJE PEDERSEN*

ABSTRACT

We find consistent value and momentum return premia across eight diverse markets and asset classes, and a strong common factor structure among their returns. Value and momentum returns correlate more strongly across asset classes than passive exposures to the asset classes, but value and momentum are negatively correlated with each other, both within and across asset classes. Our results indicate the presence of common global risks that we characterize with a three-factor model. Global funding liquidity risk is a partial source of these patterns, which are identifiable only when examining value and momentum jointly across markets. Our findings present a challenge to existing behavioral, institutional, and rational asset pricing theories that largely focus on U.S. equities.

TWO OF THE MOST studied capital market phenomena are the relation between an asset's return and the ratio of its "long-run" (or book) value relative to its current market value, termed the "value" effect, and the relation between an asset's return and its recent relative performance history, termed the "momentum" effect. The returns to value and momentum strategies have become central to the market efficiency debate and the focal points of asset pricing studies, generating numerous competing theories for their existence. We offer new insights into these two market anomalies by examining their returns jointly across eight diverse markets and asset classes. We find significant return premia to value and momentum in every asset class and strong comovement of their returns across asset classes, both of which challenge existing theories for their existence. We provide a simple three-factor model that captures the global returns across asset classes, the Fama–French U.S. stock portfolios, and a set of hedge fund indices.

*Asness is at AQR Capital Management; Moskowitz is at the University of Chicago Booth School of Business and NBER and is a consultant to AQR Capital; and Pedersen is at the New York University Stern School of Business, Copenhagen Business School, AQR, CEPR, FRIC, and NBER. We thank Aaron Brown, John Cochrane, Kent Daniel, Gene Fama, Kenneth French, Cam Harvey (the Editor), Ronen Israel, Robert Krail, John Liew, Harry Mamaysky, Michael Mendelson, Stefan Nagel, Lars Nielsen, Otto Van Hemert, Jeff Wurgler, and an anonymous referee for helpful comments, as well as seminar participants at the University of Chicago, Princeton University, Duke University, the Danish Society of Financial Analysts with Henrik Amilon and Asbjørn Trolle as discussants, and the NBER Summer Institute Asset Pricing Meetings with Kent Daniel as a discussant. We also thank Gunner Arnson, Radhika Gupta, Kelvin Hu, Sarah Jiang, Adam Klein, Ari Levine, Len Lorilla, Wes McKinney, and Karthik Sridharan for research assistance. AQR Capital invests in, among other things, value and momentum strategies. The views expressed here are those of the authors and not necessarily those of any affiliated institution.

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The literature on market anomalies predominantly focuses on U.S. individual equities, and often examines value or momentum separately. In the rare case in which value and momentum are studied outside of U.S. equities, they are also typically studied in isolation—separate from each other and separate from other markets. We uncover unique evidence and features of value and momentum by examining them jointly across eight different markets and asset classes (individual stocks in the United States, the United Kingdom, continental Europe, and Japan; country equity index futures; government bonds; currencies; and commodity futures).[1] Although some of these markets have been analyzed in isolation, our joint approach provides unique evidence on several key questions about these pervasive market phenomena. Specifically, how much variation exists in value and momentum premia across markets and asset classes? How correlated are value and momentum returns across these diverse markets and asset classes with different geographies, structures, investor types, and securities? What are the economic drivers of value and momentum premia and their correlation structure? What is a natural benchmark model for portfolios of global securities across different asset classes?

We find consistent and ubiquitous evidence of value and momentum return premia across all the markets we study, including value and momentum in government bonds and value effects in currencies and commodities, which are all novel to the literature. Our broader set of portfolios generates much larger cross-sectional dispersion in average returns than those from U.S. stocks only, providing a richer set of asset returns that any asset pricing model should seek to explain. Most strikingly, we discover significant comovement in value and momentum strategies across diverse asset classes. Value strategies are positively correlated with other value strategies across otherwise unrelated markets, and momentum strategies are positively correlated with other momentum strategies globally. However, value and momentum are negatively correlated with each other within and across asset classes.

The striking comovement pattern across asset classes is one of our central findings and suggests the presence of common global factors related to value and momentum. This common risk structure implies a set of results that we investigate further. For example, using a simple three-factor model consisting of a global market index, a zero-cost value strategy applied across all asset classes, and a zero-cost momentum strategy across all assets, we capture the comovement and the cross section of average returns both globally across asset classes and locally within an asset class. We further show that the global

[1] Early evidence on U.S. equities finds that value stocks on average outperform growth stocks (Stattman (1980), Rosenberg, Reid, and Lanstein (1985), and Fama and French (1992)) and stocks with high positive momentum (high 6- to 12-month past returns) outperform stocks with low momentum (Jegadeesh and Titman (1993), Asness (1994)). Similar effects are found in other equity markets (Fama and French (1998), Rouwenhorst (1998), Liew and Vassalou (2000), Griffin, Ji, and Martin (2003), Chui, Wei, and Titman (2010)), and in country equity indices (Asness, Liew, and Stevens (1997) and Bhojraj and Swaminathan (2006)). Momentum is also found in currencies (Shleifer and Summers (1990), Kho (1996), LeBaron (1999)) and commodities (Erb and Harvey (2006), Gorton, Hayashi, and Rouwenhorst (2008)).

three-factor model does a good job capturing the returns to the Fama and French U.S. stock portfolios as well as a set of hedge fund indices. Our use of a simple three-factor model in pricing a variety of assets globally is motivated by finance research and practice becoming increasingly global and the desire to have a single model that describes returns across asset classes rather than specialized models for each market. We show that separate factors for value and momentum best explain the data, rather than a single factor, since both strategies produce positive returns on average yet are negatively correlated.[2]

We then investigate the source of this common global factor structure. We find only modest links to macroeconomic variables such as the business cycle, consumption, and default risk. However, we find significant evidence that liquidity risk is negatively related to value and positively related to momentum globally across asset classes. Pástor and Stambaugh (2003) and Sadka (2006) find that measures of liquidity risk are positively related to momentum in U.S. individual stocks. We show that this link is also present in other markets and asset classes, and that value returns are significantly negatively related to liquidity risk globally, implying that part of the negative correlation between value and momentum is driven by opposite signed exposure to liquidity risk. Separating market from funding liquidity (see Brunnermeier and Pedersen (2009)), we further find that the primary link between value and momentum returns comes from funding risk, whose importance has increased over time, particularly after the funding crisis of 1998. Importantly, these results cannot be detected by examining a single market in isolation. The statistical power gained by looking across many markets at once—a unique feature of our analysis—allows these factor exposures to be revealed.

In terms of economic magnitudes, however, liquidity risk can only explain a small fraction of value and momentum return premia and comovement. While liquidity risk may partly explain the positive risk premium associated with momentum, because value loads negatively on liquidity risk, the positive premium associated with value becomes an even deeper puzzle. Moreover, a simple equal-weighted combination of value and momentum is immune to liquidity risk and generates substantial abnormal returns. Hence, funding liquidity risk can only provide a partial and incomplete explanation for momentum, but cannot explain the value premium or the value and momentum combination premium.

The evidence we uncover sheds light on explanations for the existence of value and momentum premia. For example, a strong correlation structure among these strategies in otherwise unrelated asset classes may indicate the presence of common global risk factors for which value and momentum premia provide compensation. Conversely, such correlation structure is not a prediction of existing behavioral models (e.g., Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999)).

[2] A single factor would require significant time variation in betas and/or risk premia to accommodate these facts. We remain agnostic as to whether our factors capture such dynamics or represent separate unconditional factors.

In addition to assuaging data mining concerns, evidence of consistent value and momentum premia across diverse asset classes may be difficult to reconcile under rational asset pricing theories that rely on firm investment risk or firm growth options as explanations for the value and momentum premia,[3] which are predominantly motivated by firm equity. These theories seem ill equipped to explain the same and correlated effects we find in currencies, government bonds, and commodities.

We also highlight that studying value and momentum jointly is more powerful than examining each in isolation. The negative correlation between value and momentum strategies and their high positive expected returns implies that a simple combination of the two is much closer to the efficient frontier than either strategy alone, and exhibits less variation across markets and over time. The return premium to a combination of value and momentum applied across all asset classes therefore presents an even bigger challenge for asset pricing theories to accommodate (e.g., Hansen and Jagannathan (1997)).

Our work also relates to the recent literature on global asset pricing. Fama and French (2012) examine the returns to size, value, and momentum in individual stocks across global equity markets and find consistent risk premia across markets. Considering both global equities and other global asset classes, Frazzini and Pedersen (2010) find consistent returns to "betting against beta," Koijen et al. (2012) document global "carry" returns, and Moskowitz, Ooi, and Pedersen (2012) present global evidence of "time series momentum." Time-series momentum is a timing strategy using each asset's own past returns, which is separate from the cross-sectional momentum strategies we study here. Focusing on this different time-series phenomenon, Moskowitz, Ooi, and Pedersen (2012) examine returns to futures contracts on equity indices, bonds, currencies, and commodities—ignoring individual stocks, which comprise half our study here—and address a different set of questions. Our focus is on the interaction between cross-sectional momentum and value strategies and their common factor structure globally, where we find striking comovement across assets and a link to liquidity risk.

The link to funding liquidity risk may also be consistent with global arbitrage activity in the face of funding constraints influencing value and momentum returns (Brunnermeier and Pedersen (2009)). Why does momentum load positively on liquidity risk and value load negatively? A simple and natural story might be that momentum represents the most popular trades, as investors chase returns and flock to the assets whose prices appreciated most recently. Value, on the other hand, represents a contrarian view. When a liquidity shock occurs, investors engaged in liquidating sell-offs (due to cash needs and risk management) will put more price pressure on the most popular and crowded trades, such as high momentum securities, as everyone runs for the exit at the

[3] See Gomes, Kogan, and Zhang (2003), Zhang (2005), Li, Livdan, and Zhang (2009), Belo (2010), Li and Zhang (2010), Liu and Zhang (2008), Berk, Green, and Naik (1999), Johnson (2002), Sagi and Seasholes (2007), and Liu, Whited, and Zhang (2009).

same time (Pedersen (2009)), while the less crowded contrarian/value trades will be less affected.

Vayanos and Wooley (2012) offer a model of value and momentum returns due to delegated management that may be consistent with these results. They argue that flows between investment funds can give rise to momentum effects from inertia due to slow moving capital, and eventually push prices away from fundamentals causing reversals or value effects. Correlation of value and momentum across different asset classes could also be affected by funds flowing simultaneously across asset classes, which could in turn be impacted by funding liquidity. However, matching the magnitude of our empirical findings remains an open question.

The paper proceeds as follows. Section I outlines our data and portfolio construction. Section II examines the performance of value and momentum across asset classes and documents their global comovement. Section III investigates the source of common variation by examining macroeconomic and liquidity risk, and Section IV offers an empirically motivated three-factor model to describe the cross section of returns across asset classes. Section V briefly discusses the robustness of our results to implementation issues. Section VI concludes by discussing the implications of our findings.

I. Data and Portfolio Construction

We describe our data and methodology for constructing value and momentum portfolios across markets and asset classes.

A. Data

A.1. Global Individual Stocks

We examine value and momentum portfolios of individual stocks globally across four equity markets: the United States, the United Kingdom, continental Europe, and Japan. The U.S. stock universe consists of all common equity in CRSP (sharecodes 10 and 11) with a book value from Compustat in the previous 6 months, and at least 12 months of past return history from January 1972 to July 2011. We exclude ADRs, REITs, financials, closed-end funds, foreign shares, and stocks with share prices less than $1 at the beginning of each month. We limit the remaining universe of stocks in each market to a very liquid set of securities that could be traded for reasonably low cost at reasonable trading volume size. Specifically, we rank stocks based on their beginning-of-month market capitalization in descending order and include in our universe the number of stocks that account cumulatively for 90% of the total market capitalization of the entire stock market.[4] This universe corresponds to an extremely liquid and tradeable set of securities. For instance, over our sample period this universe corresponds to the largest 17% of firms on average in the

[4] This procedure is similar to how MSCI defines its universe of stocks for its global stock indices.

United States. For the U.S. stock market, at the beginning of the sample period (January 1972) our universe consists of the 354 largest firms and by the end of our sample period (July 2011) the universe comprises the 676 largest names. Hence, our sample of U.S. equities is significantly larger and more liquid than the Russell 1000.

For stocks outside of the United States, we use Datastream data from the United Kingdom, continental Europe (across all European stock markets, excluding the United Kingdom), and Japan. We restrict the universe in each market using the same criteria used for U.S. stocks. On average over the sample period, our universe represents the largest 13%, 20%, and 26% of firms in the United Kingdom, Europe, and Japan, respectively. Data on prices and returns come from Datastream, and data on book values are from Worldscope.

Most studies of individual stocks examine a much broader and less liquid set of securities. We restrict our sample to a much more liquid universe (roughly the largest 20% of stocks in each market) to provide reasonable and conservative estimates of an implementable set of trading strategies and to better compare those strategies with the set of strategies we employ in index futures, currencies, government bonds, and commodity futures, which are typically more liquid instruments. Our results are conservative since value and momentum premia are larger among smaller, less liquid securities over the sample period we study.[5]

All series are monthly and end in July 2011. The U.S. and U.K. stock samples begin in January 1972. The Europe and Japan stock samples begin in January 1974. The average (minimum) number of stocks in each market over their respective sample periods is 724 (354) in the United States, 147 (76) in the United Kingdom, 290 (96) in Europe, and 471 (148) in Japan.

A.2. Global Equity Indices

The universe of country equity index futures consists of the following 18 developed equity markets: Australia, Austria, Belgium, Canada, Denmark, France, Germany, Hong Kong, Italy, Japan, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, the United Kingdom, and the United States.[6] Returns and price data as well as book values are obtained from MSCI and Bloomberg. The sample covers the period January 1978 to July 2011, with the minimum number of equity indices being 8 and all 18 indices represented

[5] Hong, Lim, and Stein (2000), Grinblatt and Moskowitz (2004), Fama and French (2012), and Israel and Moskowitz (2012) show that value and momentum returns are inversely related to the size of securities over the time period studied here, though Israel and Moskowitz (2012) show this relation is not robust for momentum in other sample periods. Value and momentum returns have also been shown to be stronger in less liquid emerging markets (Rouwenhorst (1998), Erb and Harvey (2006), Griffin, Ji, and Martin (2003)). A previous version of this paper used a broader and less liquid set of stocks that exhibited significantly stronger value and momentum returns.

[6] Austria, Belgium, Denmark, Norway, and Portugal are not index futures but are constructed from the returns of an equity index swap instrument using the respective local market index from MSCI.

after 1980. The returns on the country equity index futures do not include any returns on collateral from transacting in futures contracts, hence these are comparable to returns in excess of the risk-free rate.

A.3. Currencies

We obtain spot exchange rates from Datastream covering the following 10 currencies: Australia, Canada, Germany (spliced with the Euro), Japan, New Zealand, Norway, Sweden, Switzerland, the United Kingdom, and the United States. The data cover the period January 1979 to July 2011, where the minimum number of currencies is 7 at any point in time and all 10 currencies are available after 1980. We compute returns from currency forward contracts or MSCI spot price data and Libor rates, where currency returns are all dollar denominated and implicitly include the local interest rate differential.

A.4. Global Government Bonds

Bond index returns come from Bloomberg and Morgan Markets, short rates and 10-year government bond yields are from Bloomberg, and inflation forecasts are obtained from investment bank analysts' estimates as compiled by Consensus Economics. We obtain government bond data for the following 10 countries: Australia, Canada, Denmark, Germany, Japan, Norway, Sweden, Switzerland, the United Kingdom, and the United States over the period January 1982 to July 2011, where the minimum number of country bond returns is 5 at any point in time and all 10 country bonds are available after 1990.

A.5. Commodity Futures

We cover 27 different commodity futures obtained from several sources. Data on Aluminum, Copper, Nickel, Zinc, Lead, and Tin are from the London Metal Exchange (LME). Brent Crude and Gas Oil are from the Intercontinental Exchange (ICE). Live Cattle, Feeder Cattle, and Lean Hogs are from the Chicago Mercantile Exchange (CME). Corn, Soybeans, Soy Meal, Soy Oil, and Wheat are from the Chicago Board of Trade (CBOT). WTI Crude, RBOB Gasoline, Heating Oil, and Natural Gas are from the New York Mercantile Exchange (NYMEX). Gold and Silver are from the New York Commodities Exchange (COMEX). Cotton, Coffee, Cocoa, and Sugar are from New York Board of Trade (NYBOT), and Platinum data are from the Tokyo Commodity Exchange (TOCOM). The sample covers the period January 1972 to July 2011, with the minimum number of commodities being 10 at any point in time and all 27 commodities available after 1995.

Returns for commodity futures are calculated as follows. Each day we compute the daily excess return of the most liquid futures contract, which is typically the nearest- or next nearest-to-delivery contract, and then compound the daily returns to a total return index from which we compute returns at a monthly horizon. Bessembinder (1992), de Roon, Nijman, and Veld (2000), Moskowitz, Ooi, and Pedersen (2012), and Koijen et al. (2012) compute futures returns similarly. All returns are denominated in U.S. dollars and do not include the return on collateral associated with the futures contract.

B. Value and Momentum Measures

To measure value and momentum, we use the simplest and, to the extent a standard exists, most standard measures. We are not interested in coming up with the best predictors of returns in each asset class. Rather, our goal is to maintain a simple and fairly uniform approach that is consistent across asset classes and minimizes the pernicious effects of data snooping. As such, if data snooping can be avoided, our results may therefore understate the true gross returns to value and momentum available from more thoughtfully chosen measures.

For individual stocks, we use the common value signal of the ratio of the book value of equity to market value of equity, or book-to-market ratio, *BE/ME* (see Fama and French (1992, 1993) and Lakonishok, Shleifer, and Vishny (1994)), of the stock.[7] Book values are lagged 6 months to ensure data availability to investors at the time, and the most recent market values are used to compute the ratios. For the purposes of this paper, using lagged or contemporary prices rather than market values matched contemporaneously in time as in Fama and French (1992) is not important. When using more recent prices in the value measure, the negative correlation between value and momentum is more negative and the value premium is slightly reduced, but our conclusions are not materially affected. A combination of value and momentum—one of the themes in this paper—obtains nearly identical pricing results regardless of whether we lag price in the value measure. Asness and Frazzini (2012) investigate this issue more thoroughly and argue that using contemporaneous market values can be important and ease interpretation when examining value in the presence of momentum, as we do in this paper. Gerakos and Linnainmaa (2012) decompose value into book and market components and find that the market value of equity drives most of the relevant pricing information.

For momentum, we use the common measure of the past 12-month cumulative raw return on the asset (see Jegadeesh and Titman (1993), Asness (1994), Fama and French (1996), and Grinblatt and Moskowitz (2004)), skipping the most recent month's return, *MOM2–12*. We skip the most recent month, which is standard in the momentum literature, to avoid the 1-month reversal in stock returns, which may be related to liquidity or microstructure issues (Jegadeesh (1990), Lo and MacKinaly (1990), Boudoukh, Richardson, and Whitelaw (1994), Asness (1994), Grinblatt and Moskowitz (2004)).[8]

[7] While research has shown that other value measures are more powerful for predicting stock returns (e.g., Lakonishok, Shleifer, and Vishny (1994), Asness, Porter, and Stevens (2000), Piotroski (2000)), we maintain a basic and simple approach that is somewhat consistent across asset classes.

[8] Novy-Marx (2012) shows that the past 7- to 12-month return is a better momentum predictor in U.S. stocks than the past 2- to 6-month return, though the past 2- to 6-month return is still a

For all other asset classes, we attempt to define similar value and momentum measures. Momentum is straightforward since we can use the same measure for all asset classes, namely, the return over the past 12 months skipping the most recent month. While excluding the most recent month of returns is not necessary for some of the other asset classes we consider because they suffer less from liquidity issues (e.g., equity index futures and currencies), we do so to maintain uniformity across asset classes. Momentum returns for these asset classes are in fact stronger when we don't skip the most recent month, hence our results are conservative.

For measures of value, attaining uniformity is more difficult because not all asset classes have a measure of book value. For these assets, we try to use simple and consistent measures of value. For country indices, we use the previous month's *BE/ME* ratio for the MSCI index of the country. For commodities, we define value as the log of the spot price 5 years ago (actually, the average spot price from 4.5 to 5.5 years ago), divided by the most recent spot price, which is essentially the negative of the spot return over the last 5 years. Similarly, for currencies, our value measure is the negative of the 5-year return on the exchange rate, measured as the log of the average spot exchange rate from 4.5 to 5.5 years ago divided by the spot exchange rate today minus the log difference in the change in CPI in the foreign country relative to the U.S. over the same period. The currency value measure is therefore the 5-year change in purchasing power parity. For bonds, we use the 5-year change in the yields of 10-year bonds as our value measure, which is similar to the negative of the past 5-year return. These long-term past return measures of value are motivated by DeBondt and Thaler (1985), who use similar measures for individual stocks to identify "cheap" and "expensive" firms. Fama and French (1996) show that the negative of the past 5-year return generates portfolios that are highly correlated with portfolios formed on *BE/ME*, and Gerakos and Linnainmaa (2012) document a direct link between past returns and *BE/ME* ratios. Theory also suggests a link between long-term returns and book-to-market value measures (e.g., Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), Hong and Stein (1999), and Vayanos and Wooley (2012)).

In the Internet Appendix accompanying this paper, we show that individual stock portfolios formed from the negative of past 5-year returns are highly correlated with those formed on *BE/ME* ratios in our sample.[9] For example,

positive predictor. We use the more standard momentum measure based on the past 2- to 12-month return for several reasons. First, as Novy-Marx (2012) shows, the benefit of using returns from the past 7- to 12-months as opposed to the entire 2- to 12-month past return is negligible in U.S. stocks. Second, Goyal and Wahal (2012) examine the power of past 7- to 12-month versus past 2- to 6-month returns across 36 countries and find that there is no significant difference between these past return predictors in 35 out of 36 countries—the exception being the United States. Third, *MOM2–12* is the established momentum signal that has worked well out of sample over time and across geography. While we believe using *MOM2–12* is the most prudent and reasonable measure to use for these reasons, using other momentum signals, such as *MOM7–12*, should not alter any of our conclusions.

[9] An Internet Appendix may be found in the online version of this article.

among U.S. stocks the correlation between returns to a value factor formed from the negative of the past 5-year return and the returns formed from *BE/ME* sorts is 0.83. In the United Kingdom, Europe, and Japan the correlation between portfolio returns formed on negative past 5-year returns and *BE/ME* ratios is similarly high. Globally, a value factor averaged across all four stock markets estimated from negative past 5-year return sorts has a correlation of 0.86 with a value factor formed from *BE/ME* sorts. Hence, using past 5-year returns to measure value seems reasonable.

C. Value and Momentum Portfolios: 48 New Test Assets

Using the measures above, we construct a set of value and momentum portfolios within each market and asset class by ranking securities within each asset class by value or momentum and sorting them into three equal groups. We then form three portfolios—high, middle, and low—from these groups, where for individual stocks we value weight the returns in the portfolios by their beginning-of-month market capitalization, and for the nonstock asset classes we equal weight securities.[10] Given that our sample of stocks focuses exclusively on very large and liquid securities in each market, typically the largest quintile of securities, further value weighting the securities within this universe creates an extremely large and liquid set of portfolios that should yield very conservative results compared to typical portfolios used in the literature. Thus, we generate three portfolios—low, middle, and high—for each of the two characteristics—value and momentum—in each of the eight asset classes, producing $3 \times 2 \times 8 = 48$ test portfolios.

D. Value and Momentum Factors

We also construct value and momentum factors for each asset class, which are zero-cost long-short portfolios that use the entire cross section of securities within an asset class. For any security $i = 1, \ldots, N$ at time t with signal S_{it} (value or momentum), we weight securities in proportion to their cross-sectional rank based on the signal minus the cross-sectional average rank of that signal. Simply using ranks of the signals as portfolio weights helps mitigate the influence of outliers, but portfolios constructed using the raw signals are similar and generate slightly better performance. Specifically, the weight on security i at time t is

$$w_{it}^S = c_t(\text{rank}(S_{it}) - \Sigma_i \text{rank}(S_{it})/N), \tag{1}$$

where the weights across all stocks sum to zero, representing a dollar-neutral long-short portfolio. We include a scaling factor c_t such that the overall portfolio is scaled to one dollar long and one dollar short. The return on the portfolio is

[10] Weighting the nonstock asset classes by their ex ante volatility gives similar results. In addition, rebalancing back to equal weights annually rather than monthly produces similar results.

then

$$r_t^S = \Sigma_i w_{it}^S r_{it}, \quad \text{where } S \in (\text{value, momentum}). \tag{2}$$

We also construct a 50/50 equal combination (*COMBO*) factor of value and momentum, whose returns are

$$r_t^{COMBO} = 0.5 r_t^{VALUE} + 0.5 r_t^{MOM}. \tag{3}$$

These zero-cost signal-weighted portfolios are another way to examine the efficacy of value and momentum across markets and are used as factors in our pricing model. Although these factors are not value weighted, the set of securities used to generate them are extremely large and liquid. As we will show, the signal-weighted factor portfolios outperform simple portfolio sort spreads because security weights are a positive (linear) function of the signal, as opposed to the coarseness of only classifying securities into three groups. In addition, the factors are better diversified since more securities in the cross section are given nonzero weight and the weights are less extreme.

II. Value and Momentum Returns and Comovement

Table I shows the consistent performance of value and momentum, and their combination, within each of the major markets and asset classes we study. Other studies examine value and momentum in some of the same asset classes, but not in combination and not simultaneously across asset classes as we do here. In addition, we also discover new evidence for value and momentum premia in asset classes not previously studied—both value and momentum in government bonds and value effects in currencies and commodities. Our emphasis, however, is on the power of applying value and momentum everywhere at once.

A. Return Premia

Table I reports the annualized mean return, t-statistic of the mean, standard deviation, and Sharpe ratio of the low (P1), middle (P2), and high (P3) portfolios for value and momentum in each market and asset class as well as the high minus low (P3-P1) spread portfolio and the signal-weighted factor portfolio from equation (2). Also reported are the intercepts or alphas, and their t-statistics (in parentheses) from a time-series regression of each return series on the return of the market index for each asset class. The market index for the stock strategies is the MSCI equity index for each country; for country index futures it is the MSCI World Index; and for currencies, fixed income, and commodities, the benchmark is an equal-weighted basket of the securities in each asset class. The last two columns of Table I report the same statistics for the 50/50 combination of value and momentum for the P3-P1 spread and signal-weighted factors (following equations (2) and (3)), and the last row for each asset class reports the correlation of returns between value and momentum for both

Table I

Performance of Value and Momentum Portfolios across Markets and Asset Classes

Reported are the average raw excess (of the 1-month U.S. T-bill rate) return, t-statistic of the average return (in parentheses), standard deviation of returns, and Sharpe ratio of each value, momentum, and equal-weighted 50/50 value and momentum combination strategy in each market and asset class we study: U.S. stocks, U.K. stocks, Europe stocks, Japan stocks, country index futures, currencies, fixed income government bonds, and commodities. Also reported are the intercepts or alphas, and their t-statistics (in parentheses) from a time-series regression of each return series on the return of the market index for each asset class. The market index for the stock strategies is the MSCI equity index for each country for all of the individual stock strategies. The MSCI world index is used as the benchmark for strategies of country index futures. For currencies, fixed income, and commodities, the benchmark index is an equal-weighted basket of the securities in each asset class. In each market or asset class the universe of securities is first sorted by either value or momentum and then broken into three equal groups based on those sorts to form three portfolios—low, middle, and high—corresponding to portfolios P1, P2, and P3, respectively. For individual stock strategies (Panel A), stocks within the three portfolios are value weighted by their beginning-of-month capitalization, and for nonstock asset classes (Panel B), securities are equal weighted in the portfolios. Also reported is the high minus low spread in returns (P3-P1) as well as a rank-weighted factor portfolio ("Factor"), which is a zero-investment portfolio that weights each asset in proportion to its rank based on either value or momentum, following equation (1). The 50/50 value/momentum combination strategies are an equal-weighted average of the value and momentum spread strategies (P3–P1 and Factor) for each market/asset class. Results are also reported for an average of all individual stock strategies across all stock markets ("Global stocks"), across all nonstock asset classes ("Global other asset classes"), and across all markets and asset classes ("Global all asset classes"), where average return series are computed using equal volatility weights across the markets and asset classes to account for the large differences in volatility across asset classes (e.g., fixed income vs. commodities). Panel C also reports results for alternative measures of value for fixed income securities. Finally, the last row for each asset class reports the correlation between value and momentum zero cost residual returns from the benchmark in each market or asset class. Statistics are computed from monthly return series but are reported as annualized numbers.

Panel A: Individual Stock Portfolios

		Value Portfolios					Momentum Portfolios					50/50 Combination	
		P1	P2	P3	P3–P1	Factor	P1	P2	P3	P3–P1	Factor	P3–P1	Factor
U.S. stocks	Mean	9.5%	10.6%	13.2%	3.7%	3.9%	8.8%	9.7%	14.2%	5.4%	7.7%	4.6%	5.8%
01/1972 to	(t-stat)	(3.31)	(4.33)	(5.19)	(1.83)	(1.66)	(2.96)	(4.14)	(4.82)	(2.08)	(2.84)	(3.98)	(5.40)
07/2011	Stdev	17.9%	15.4%	15.9%	12.8%	14.8%	18.6%	14.8%	18.5%	16.4%	17.0%	7.2%	6.8%
	Sharpe	0.53	0.69	0.83	0.29	0.26	0.47	0.66	0.77	0.33	0.45	0.63	0.86
	Alpha	−1.7%	0.8%	3.6%	5.3%	5.8%	−2.3%	0.2%	3.7%	6.0%	8.7%	5.7%	7.2%
	(t-stat)	(−1.59)	(1.02)	(3.17)	(2.66)	(2.49)	(−1.68)	(0.29)	(2.34)	(2.30)	(3.22)	(5.05)	(7.06)
									Correlation (Val, Mom) =			−0.53	−0.65

(*Continued*)

Table I—*Continued*

Panel A: Individual Stock Portfolios

		Value Portfolios					Momentum Portfolios					50/50 Combination	
		P1	P2	P3	P3–P1	Factor	P1	P2	P3	P3–P1	Factor	P3–P1	Factor
U.K. stocks	Mean	10.8%	12.5%	15.3%	4.5%	5.5%	9.2%	13.8%	15.2%	6.0%	7.2%	6.3%	7.2%
01/1972 to	(*t*-stat)	(3.17)	(3.48)	(4.12)	(1.83)	(2.10)	(2.32)	(3.81)	(4.04)	(2.37)	(3.00)	(4.23)	(5.85)
07/2011	Stdev	18.6%	19.7%	20.3%	13.4%	14.4%	24.9%	22.7%	23.7%	15.9%	15.0%	8.1%	6.7%
	Sharpe	0.58	0.64	0.75	0.33	0.38	0.37	0.61	0.64	0.38	0.48	0.77	1.07
	Alpha	– 0.2%	0.5%	3.2%	3.5%	4.4%	– 3.2%	2.1%	3.5%	6.7%	8.0%	6.0%	7.2%
	(*t*-stat)	(– 0.17)	(0.42)	(2.03)	(1.47)	(1.74)	(– 2.13)	(2.06)	(2.31)	(2.66)	(3.36)	(4.05)	(5.84)
									Correlation (Val, Mom) =			– 0.43	– 0.62
Europe stocks	Mean	11.8%	14.6%	16.7%	4.8%	5.2%	9.2%	13.3%	17.3%	8.1%	9.8%	5.9%	6.9%
01/1974 to	(*t*-stat)	(3.53)	(4.43)	(4.61)	(2.32)	(2.95)	(2.72)	(4.65)	(5.56)	(3.37)	(4.59)	(4.77)	(6.55)
07/2011	Stdev	18.3%	18.0%	19.8%	11.5%	9.7%	20.6%	17.5%	19.0%	14.7%	13.1%	6.8%	5.8%
	Sharpe	0.64	0.81	0.84	0.42	0.54	0.44	0.76	0.91	0.55	0.75	0.87	1.20
	Alpha	– 0.4%	2.2%	3.1%	3.5%	4.0%	– 3.5%	2.2%	6.0%	9.1%	10.7%	6.1%	7.1%
	(*t*-stat)	(– 0.30)	(2.06)	(2.57)	(1.71)	(2.32)	(– 2.54)	(2.39)	(4.18)	(3.88)	(5.05)	(4.88)	(6.77)
									Correlation (Val, Mom) =			– 0.52	– 0.55
Japan stocks	Mean	2.6%	8.2%	14.7%	12.0%	10.2%	8.4%	9.9%	10.1%	1.7%	2.2%	6.4%	5.9%
01/1974 to	(*t*-stat)	(0.61)	(2.02)	(3.69)	(4.31)	(4.22)	(2.19)	(2.94)	(2.69)	(0.57)	(0.81)	(4.28)	(4.80)
07/2011	Stdev	23.6%	22.1%	21.8%	15.3%	13.2%	23.5%	20.6%	23.1%	18.6%	16.5%	8.1%	6.7%
	Sharpe	0.11	0.37	0.67	0.79	0.77	0.36	0.48	0.44	0.09	0.13	0.78	0.88
	Alpha	– 5.6%	0.1%	7.3%	13.0%	10.7%	– 1.1%	0.8%	0.5%	1.7%	2.2%	6.8%	6.1%
	(*t*-stat)	(– 3.36)	(0.12)	(3.95)	(4.71)	(4.47)	(– 0.59)	(0.73)	(0.31)	(0.54)	(0.84)	(4.63)	(5.05)
									Correlation (Val, Mom) =			– 0.60	– 0.64

(*Continued*)

Table I—*Continued*

		Value Portfolios					Momentum Portfolios					50/50 Combination	
		P1	P2	P3	P3–P1	Factor	P1	P2	P3	P3–P1	Factor	P3–P1	Factor
Panel A: Individual Stock Portfolios													
Global stocks	Mean	8.1%	11.0%	14.6%	6.2%	5.8%	8.5%	11.1%	14.1%	5.6%	7.1%	6.3%	6.8%
01/1972 to	(t-stat)	(3.17)	(4.54)	(5.84)	(3.60)	(3.18)	(3.10)	(4.82)	(5.46)	(2.94)	(3.73)	(6.52)	(8.04)
07/2011	Stdev	16.6%	15.2%	15.7%	10.9%	11.4%	17.1%	14.5%	16.2%	12.0%	12.0%	6.1%	5.3%
	Sharpe	0.50	0.72	0.93	0.57	0.51	0.49	0.77	0.87	0.47	0.59	1.04	1.28
	Alpha	−2.3%	0.7%	4.2%	6.6%	6.1%	−3.3%	0.5%	3.1%	6.4%	8.1%	6.8%	7.5%
	(t-stat)	(−1.70)	(0.69)	(3.49)	(3.79)	(3.37)	(−3.00)	(1.00)	(2.78)	(3.37)	(4.31)	(7.09)	(8.98)
										Correlation (Val, Mom) =		−0.52	−0.60
Panel B: Other Asset Class Portfolios													
Country indices	Mean	3.1%	6.6%	9.1%	6.0%	5.7%	2.3%	5.8%	11.0%	8.7%	7.4%	7.3%	10.6%
01/1978 to	(t-stat)	(1.10)	(2.40)	(3.20)	(3.45)	(3.40)	(0.81)	(2.13)	(3.72)	(4.14)	(3.57)	(6.62)	(5.72)
07/2011	Stdev	16.2%	15.7%	16.2%	9.8%	9.5%	16.2%	15.4%	16.8%	11.9%	11.8%	6.3%	10.6%
	Sharpe	0.19	0.42	0.56	0.61	0.60	0.14	0.37	0.65	0.73	0.63	1.16	1.00
	Alpha	−3.2%	0.5%	2.7%	5.9%	5.3%	−3.9%	−0.3%	4.4%	8.2%	7.1%	7.1%	10.0%
	(t-stat)	(−3.24)	(0.48)	(2.76)	(3.45)	(3.24)	(−3.41)	(−0.40)	(4.00)	(4.00)	(3.47)	(6.49)	(5.47)
										Correlation (Val, Mom) =		−0.34	−0.37
Currencies	Mean	−0.5%	0.3%	2.8%	3.3%	3.9%	−0.7%	0.3%	2.8%	3.5%	3.0%	3.4%	5.6%
01/1979 to	(t-stat)	(−0.30)	(0.23)	(1.98)	(1.89)	(2.47)	(−0.40)	(0.20)	(1.91)	(1.90)	(1.77)	(3.51)	(3.89)
07/2011	Stdev	9.2%	8.3%	7.9%	9.7%	9.0%	9.4%	8.0%	8.2%	10.3%	9.6%	5.4%	8.0%
	Sharpe	−0.05	0.04	0.35	0.34	0.44	−0.07	0.04	0.34	0.34	0.32	0.63	0.69
	Alpha	−1.4%	−0.6%	2.0%	3.4%	4.1%	−1.6%	−0.6%	2.0%	3.6%	3.1%	3.5%	5.7%
	(t-stat)	(−1.53)	(−0.94)	(2.25)	(2.04)	(2.63)	(−1.58)	(−1.01)	(2.18)	(1.99)	(1.84)	(3.83)	(4.11)
										Correlation (Val, Mom) =		−0.42	−0.43

(*Continued*)

Table I—*Continued*

Panel B: Other Asset Class Portfolios

		Value Portfolios					Momentum Portfolios					50/50 Combination	
		P1	P2	P3	P3–P1	Factor	P1	P2	P3	P3–P1	Factor	P3–P1	Factor
Fixed income 01/1982 to 07/2011	Mean	3.0%	4.0%	4.2%	1.1%	0.5%	3.8%	3.8%	4.2%	0.4%	1.0%	0.8%	0.7%
	(*t*-stat)	(2.31)	(3.58)	(3.76)	(0.97)	(0.39)	(3.42)	(3.49)	(3.28)	(0.35)	(0.88)	(1.03)	(1.08)
	Stdev	7.0%	5.9%	5.9%	6.3%	6.4%	5.9%	5.9%	6.8%	6.0%	5.8%	4.0%	3.5%
	Sharpe	0.43	0.67	0.71	0.18	0.07	0.64	0.66	0.61	0.06	0.17	0.19	0.20
	Alpha	−1.3%	0.3%	0.7%	1.9%	1.4%	0.2%	0.3%	−0.1%	−0.3%	0.1%	0.8%	0.7%
	(*t*-stat)	(−1.87)	(0.51)	(1.03)	(1.68)	(1.21)	(0.34)	(0.48)	(−0.17)	(−0.29)	(0.08)	(1.10)	(1.15)
									Correlation (Val, Mom) =			−0.17	−0.35
Commodities 01/1972 to 07/2011	Mean	4.2%	4.1%	10.5%	6.3%	7.3%	0.7%	5.8%	13.1%	12.4%	11.5%	9.4%	17.1%
	(*t*-stat)	(1.21)	(1.34)	(3.50)	(1.61)	(1.92)	(0.22)	(2.27)	(3.73)	(3.29)	(3.14)	(4.42)	(4.78)
	Stdev	21.5%	18.8%	18.5%	24.2%	23.7%	19.0%	15.9%	21.8%	23.4%	22.8%	13.1%	22.2%
	Sharpe	0.19	0.22	0.57	0.26	0.31	0.04	0.37	0.60	0.53	0.51	0.71	0.77
	Alpha	−2.9%	−2.4%	4.8%	7.7%	8.2%	−5.6%	0.4%	5.8%	11.4%	10.5%	9.5%	17.1%
	(*t*-stat)	(−1.39)	(−1.39)	(2.34)	(2.02)	(2.19)	(−2.95)	(0.26)	(2.71)	(3.06)	(2.89)	(4.57)	(4.82)
									Correlation (Val, Mom) =			−0.39	−0.46
Global other asset classes 01/1972 to 07/2011	Mean	2.2%	3.1%	5.7%	3.4%	3.6%	1.6%	3.4%	6.3%	4.6%	4.4%	4.0%	6.8%
	(*t*-stat)	(1.88)	(2.97)	(5.63)	(3.08)	(3.42)	(1.49)	(3.61)	(5.30)	(3.88)	(3.83)	(6.39)	(7.03)
	Stdev	7.3%	6.4%	6.2%	6.4%	6.6%	6.7%	5.9%	7.3%	7.4%	7.1%	3.9%	6.0%
	Sharpe	0.30	0.48	0.91	0.50	0.55	0.24	0.58	0.85	0.63	0.62	1.03	1.14
	Alpha	−1.0%	−0.1%	3.0%	4.0%	3.9%	−1.4%	−0.7%	3.1%	4.5%	4.1%	4.2%	6.8%
	(*t*-stat)	(−1.26)	(−0.18)	(4.10)	(3.67)	(3.71)	(−1.85)	(−1.07)	(3.65)	(3.80)	(3.62)	(6.83)	(7.12)
									Correlation (Val, Mom) =			−0.40	−0.49
Global all asset classes 01/1972 to 07/2011	Mean	4.5%	6.1%	9.1%	4.6%	4.6%	4.2%	6.4%	9.2%	5.0%	5.4%	5.0%	6.8%
	(*t*-stat)	(3.00)	(4.42)	(6.47)	(4.55)	(4.47)	(2.74)	(4.88)	(6.09)	(4.18)	(4.59)	(8.77)	(9.83)
	Stdev	9.3%	8.5%	8.7%	6.3%	6.4%	9.5%	8.1%	9.4%	7.5%	7.4%	3.5%	4.3%
	Sharpe	0.48	0.71	1.04	0.73	0.72	0.44	0.79	0.98	0.67	0.74	1.42	1.59
	Alpha	−2.0%	−0.2%	2.9%	4.8%	4.8%	−2.6%	0.3%	2.6%	5.2%	5.6%	5.0%	6.9%
	(*t*-stat)	(−2.29)	(−0.35)	(3.71)	(4.81)	(4.69)	(−3.07)	(0.43)	(3.04)	(4.34)	(4.76)	(9.00)	(10.03)
									Correlation (Val, Mom) =			−0.53	−0.60

(*Continued*)

Table I—*Continued*

Panel C: Alternative Value Measures for Fixed Income

		Value Portfolios					50-50 Combination	
Fixed income 01/1983 to 07/2011		P1	P2	P3	P3–P1	Factor	P3–P1	Factor
Value = 5-year yield change (yield to yield 5 years ago)	Mean	3.0%	4.0%	4.2%	1.1%	0.5%	0.8%	0.7%
	(*t*-stat)	(2.31)	(3.58)	(3.76)	(0.97)	(0.39)	(1.03)	(1.08)
	Stdev	7.0%	5.9%	5.9%	6.3%	6.4%	4.0%	3.5%
	Sharpe	0.43	0.67	0.71	0.18	0.07	0.19	0.20
	Alpha	−1.3%	0.3%	0.7%	1.9%	1.4%	0.8%	0.7%
	(*t*-stat)	(−1.87)	(−0.51)	(1.03)	(1.68)	(1.21)	(1.10)	(1.15)
					Correlation (Val, Mom) =		−0.17	−0.35
Value = real bond yield (10-year yield to 5-year inflation forecast)	Mean	0.9%	2.1%	2.9%	2.0%	1.9%	0.9%	1.4%
	(*t*-stat)	(1.84)	(3.36)	(4.17)	(3.78)	(3.58)	(2.44)	(2.63)
	Stdev	2.6%	3.2%	3.6%	2.7%	2.8%	1.9%	2.9%
	Sharpe	0.36	0.65	0.81	0.73	0.70	0.46	0.49
	Alpha	−0.6%	−0.1%	0.4%	1.0%	0.9%	0.4%	0.6%
	(*t*-stat)	(−2.02)	(−0.15)	(1.09)	(2.36)	(2.09)	(1.17)	(1.25)
					Correlation (Val, Mom) =		−0.09	−0.03
Value = term spread (10-year yield to short rate)	Mean	0.8%	1.5%	2.3%	1.5%	1.7%	0.6%	1.1%
	(*t*-stat)	(1.25)	(2.37)	(3.60)	(2.69)	(3.22)	(1.47)	(1.96)
	Stdev	3.2%	3.2%	3.2%	2.8%	2.5%	2.2%	2.9%
	Sharpe	0.25	0.250.48	0.73	0.55	0.65	0.28	0.37
	Alpha	−1.2%	−0.7%	0.1%	1.3%	1.4%	0.5%	0.8%
	(*t*-stat)	(−3.03)	(−1.79)	(0.28)	(2.78)	(3.31)	(1.22)	(1.55)
					Correlation (Val, Mom) =		0.22	0.28
Value = composite average of all three measures	Mean	0.3%	1.6%	3.0%	2.6%	2.9%	1.3%	2.2%
	(*t*-stat)	(0.58)	(2.56)	(4.63)	(4.88)	(5.89)	(3.17)	(4.30)
	Stdev	3.2%	3.4%	3.4%	2.9%	2.6%	2.1%	2.7%
	Sharpe	0.11	0.48	0.87	0.91	1.10	0.59	0.81
	Alpha	−1.5%	−0.3%	0.8%	2.3%	2.6%	1.0%	1.8%
	(*t*-stat)	(−4.01)	(−0.80)	(2.25)	(4.40)	(5.48)	(2.55)	(3.66)
					Correlation (Val, Mom) =		0.03	0.04

the P3-P1 zero-cost spread portfolio and the zero-cost signal-weighted factor returns.

Panel A of Table I reports results for each of the individual stock strategies. Consistent with results in the literature, there is a significant return premium for value in every stock market, with the strongest performance in Japan. Momentum premia are also positive in every market, especially in Europe, but are statistically insignificant in Japan. As the last row for each market indicates, the correlation between value and momentum returns is strongly negative, averaging about –0.60. Combining two positive return strategies with such strong negative correlation to each other increases Sharpe ratios significantly. In every market, the value/momentum combination outperforms either value or momentum by itself. Hence, many theories attempting to explain the observed Sharpe ratio for value or momentum have a higher hurdle to meet if considering a simple linear combination of the two.

In addition, the combination of value and momentum is much more stable across markets. For instance, previous research attempting to explain why momentum does not work very well in Japan (see Chui, Titman, and Wei (2010) for a behavioral explanation related to cultural biases) needs to confront the fact that value has performed exceptionally well in Japan during the same time period, as well as the fact that the correlation between value and momentum in Japan is –0.64 over this period. So, rather than explain why momentum did not work in Japan, it would be nearly equally appropriate to ask why value did so well (see Asness (2011)). Moreover, an equal combination of value and momentum in Japan realizes an even higher Sharpe ratio than value alone suggesting that a positive weight on momentum in Japan improves the efficient frontier, which is also confirmed from a static portfolio optimization.

The last set of rows of Table I, Panel A show the power of combining value and momentum portfolios across markets. We report an average of value, momentum, and their combination across all four regions ("Global stocks") by weighting each market by the inverse of their ex post sample standard deviation.[11] Value applied globally generates an annualized Sharpe ratio not much larger than the average of the Sharpe ratios across each market, indicating strong covariation among value strategies across markets. Likewise, momentum applied globally does not produce a Sharpe ratio much larger than the

[11] We compute the monthly standard deviation of returns for each passive benchmark in each market and weight each market by the inverse of this number, rescaled to sum to one, to form a global portfolio across all markets. Each market's dollar contribution to the global portfolio is therefore proportional to the reciprocal of its measured volatility, but each market contributes an equal fraction to the total volatility of the portfolio, ignoring correlations. We weight every portfolio (low, middle, high, and value and momentum) and factor within each market by the same number based on of the volatility of the total market index for that market. For the nonstock asset classes we do the same, where the benchmark portfolio is simply an equal weighted average of all the securities in that asset class. Weighting by total market cap or equal weighting produces nearly identical results, but we use the equal volatility weighting scheme to be consistent with our procedure for the nonequity asset classes, where market cap has no meaning and where volatility differs greatly across different asset clasees.

average Sharpe ratio across markets, indicating strong correlation structure among momentum portfolios globally, too.

Panel B of Table I reports the same statistics for the nonstock asset classes. There are consistent value and momentum return premia in these asset classes as well, including some not previously examined (e.g., bonds, value in currencies and commodities).[12] While value and momentum returns vary somewhat across the asset classes, the combination of value and momentum is quite robust due to a consistent negative correlation between value and momentum within each asset class that averages –0.49. We also examine a diversified portfolio of value, momentum, and their combination across all asset classes. Since the volatilities of the portfolios are vastly different across asset classes—for example, commodity strategies have about four times the volatility of bond strategies—we weight each asset class by the inverse of its ex post sample volatility, so that each asset class contributes roughly an equal amount to the ex post volatility of the diversified portfolio.[13] The diversified portfolio across all asset classes yields small improvements in Sharpe ratios, which suggests the presence of correlation structure in value and momentum returns across these different asset classes. Models that give rise to value and momentum returns in equities, such as the production- or investment-based theories of Berk, Green, and Naik (1999), Johnson (2002), Gomes, Kogan, and Zhang (2003), Zhang (2005), Sagi and Seasholes (2007), Liu, Whited, and Zhang (2009), Li, Livdan, and Zhang (2009), Belo (2010), Li and Zhang (2010), and Liu and Zhang (2008), may not easily apply to other asset classes, yet we find similar value and momentum effects that are correlated to those found in equities, suggesting at least part of these premia are not captured by these models. Likewise, theories of investor behavior, which largely rely on individual investors in equities, will also have difficulty accommodating these facts.

Combining the stock (Panel A) and nonstock (Panel B) value and momentum strategies across all asset classes produces even larger Sharpe ratios. We combine the global stock strategies with the global nonstock other asset class strategies by weighting each by the inverse of their in-sample volatility, where we weight the average stock strategy by its volatility and the average nonstock strategy by its volatility, rather than weighting each individual market or asset class by its own volatility. The 50/50 value and momentum combination portfolio produces an annual Sharpe ratio of 1.45, which presents an even greater challenge for asset pricing models that already struggle to explain the magnitude of the U.S. equity premium, which is about one third as large. Considering value and momentum together and applying them globally across all asset classes, the Sharpe ratio hurdle that these pricing models need to explain is several times larger than those found in U.S. equity data alone.

[12] The somewhat weaker returns for the nonstock asset classes would be partially attenuated if transactions costs were considered, since trading costs are typically higher for individual stocks than the futures contracts we examine outside of equities. Therefore, net-of-trading-cost returns would elevate the relative importance of the nonstock strategies. We discuss implementation issues briefly in Section V.

[13] Using ex ante rolling measures of volatility and covariances yields similar results.

B. Alternative Measures

We use a single measure for value and a single measure for momentum for all eight markets we study. We choose the most studied or simplest measure in each case and attempt to maintain uniformity across asset classes to minimize the potential for data mining. Using these simple, uniform measures results in positive risk premia for value and momentum in every asset class we study, though some of the results are statistically insignificant. In particular, our weakest results pertain to bonds, which do not produce statistically reliable premia. However, data mining worries may be weighed against the potential improvements from having better measures of value and momentum. For example, value strategies among bonds can be markedly improved with more thoughtful measures. Using our current measure of value, the 5-year change in yields of 10-year maturity bonds, we are only able to produce a Sharpe ratio of 0.18 and an alpha of 1.9% that is not statistically significant (t-statistic of 1.68). However, Panel C of Table I reports results for value strategies among bonds that use alternative measures, such as the real bond yield, which is the yield on 10-year bonds minus the 5-year forecast in inflation, and the term spread, which is the yield on 10-year bonds minus the short rate. As Panel C of Table I shows, these alternative value measures produce Sharpe ratios of 0.73 and 0.55, respectively, and the t-statistics of their alphas are significant at 2.36 and 2.78.

Moreover, we are able to produce even more reliable risk premia when using multiple measures of value simultaneously that diversify away measurement error and noise across the variables.[14] Creating a composite average index of value measures using all three measures above produces even stronger results, where value strategies generate Sharpe ratios of 0.91 and 1.10 with t-statistics on their alphas of 4.40 and 5.48. These alternative measures of value also blend nicely with our original measure for momentum, where, in each case, the 50/50 value/momentum combination portfolios also improve with these alternative measures.

Hence, our use of single, simple, and uniform value and momentum measures may understate the true returns to these strategies in each asset class. Nevertheless, we stick with these simple measures to be conservative and to mitigate data mining concerns, even though, in the case of bonds, the results appear to be insignificant with such simple measures.

C. Comovement across Asset Classes

Table II reports the correlations of value and momentum returns across diverse asset classes to identify their common movements. The strength of comovement may support or challenge various theoretical explanations for value and momentum, and may ultimately point to underlying economic drivers

[14] Israel and Moskowitz (2012) show how other measures of value and momentum can improve the stability of returns to these styles among individual equities.

Table II

Correlation of Value and Momentum Strategies across Markets and Asset Classes

Reported are the average correlations among all value and momentum strategies across markets and asset classes. Panel A reports the correlations of the average return series, where we first compute the average return series for a group (e.g., all individual stock value strategies across all markets and all nonstock value strategies across all nonstock asset classes) and then compute the correlation between the two average return series. The diagonal elements in Panel A are computed as the average correlation between each market's return series and the average of all other return series in other markets, excluding the market itself. For example, we compute the correlation between U.S. stock value returns and the average returns to value strategies across stocks in the United Kingdom, Europe, and Japan. We then do the same for U.K. value returns with the average of value returns across the United States, Europe, and Japan, and repeat this for Europe value and Japan value strategies as well. We then take the average of these correlations and report them as the first diagonal element of Panel A. Correlations are computed from quarterly returns to mitigate the influence of nonsynchronous trading across markets. Panel B breaks down the correlations of the individual stock value and momentum strategies series with each of the nonstock value and momentum strategies. An F-test for the joint significance of the individual correlations within each group is performed, where * indicates the correlations are significantly different from zero at the 5% significance level.

Panel A: Correlation of Average Return Series

	Stock Value	Nonstock Value	Stock Momentum	Nonstock Momentum
Stock value	0.68*	0.15*	−0.53*	−0.26*
Nonstock value		0.07	−0.16*	−0.13*
Stock momentum			0.65*	0.37*
Nonstock momentum				0.21*

Panel B: Correlation of Average Stock Series with Each Nonstock Series

	Country Index Value	Currency Value	Fixed Income Value	Commodity Value	Country Index Momentum	Currency Momentum	Fixed Income Momentum	Commodity Momentum
Global Stock value	0.27*	0.13*	−0.03	0.01	−0.28*	−0.20*	−0.01	−0.17*
Global Stock momentum	−0.19*	−0.12*	−0.05	−0.06	0.40*	0.28*	0.09	0.20*

for their returns. The correlations are computed from the returns of the signal-weighted zero-cost factor portfolios from equation (2), but results are similar using the top third minus bottom third P3-P1 portfolio returns.

Panel A of Table II reports the correlations among value strategies and among momentum strategies globally across asset markets. We first compute the average return series for value and momentum across all stock markets and across all nonstock asset classes separately. For example, we compute the volatility-weighted average of all the individual stock value strategies across the four equity markets—the United States, the United Kingdom, Europe, and Japan—and the weighted average of the value strategies across the nonequity asset classes—index futures, currencies, bonds, and commodities. We do the same for momentum. We then compute the correlation matrix between these average return series. The diagonal of the correlation matrix is computed as the average correlation between each individual market's return series and the average of all *other* return series in other markets. For instance, the first entry in the covariance matrix is the average of the correlations between each equity market's value strategy and a portfolio of all other equity market value strategies: an average of the correlation of U.S. value with a diversified value strategy in all other individual equity markets (United Kingdom, Europe, and Japan); the correlation of U.K. value with a diversified value strategy in the United States, Europe, and Japan; the correlation of Europe value with a diversified value strategy in the United States, the United Kingdom, and Japan; and the correlation of Japan value with a diversified value strategy in the United States, United Kingdom, and Europe. We then take an equal weighted average of these four correlations to get the first element of the correlation matrix in Panel A of Table II. In general, we obtain more powerful statistical findings when looking at the correlations of the average return series rather than the average of individual correlations, since the former better diversifies away random noise from each market, a theme we emphasize throughout the paper.[15] Correlations are computed from quarterly returns to help mitigate any nonsynchronous trading issues across markets, due to illiquid assets that do not trade continuously or time zone differences. An F-test on the joint significance of the correlations is also performed.

Panel A of Table II shows a consistent pattern, where value in one market or asset class is positively correlated with value elsewhere, momentum in one market or asset class is positively correlated with momentum elsewhere, and value and momentum are negatively correlated everywhere across markets and asset classes. The average individual stock value strategy has a correlation of

[15] In the Internet Appendix to the paper, we report the average of the individual correlations among the stock and nonstock value and momentum strategies, where we first compute the pairwise correlations of all individual strategies (e.g., U.S. value with Japan value) and then take the average for each group. We exclude the correlation of each strategy with itself (removing the 1s) when averaging and also exclude the correlation of each strategy with all other strategies within the same market (i.e., exclude U.S. momentum when examining U.S. value's correlation with other momentum strategies). While these individual correlations are consistently weaker than those obtained from taking averages first and then computing correlations, the average pairwise correlations also exhibit strong comovement among value and momentum across markets.

0.68 with the average value strategy in other stock markets, and of 0.15 with the average nonstock value strategy. The average individual stock momentum strategy has a correlation of 0.65 with the average momentum strategy in other stock markets and a correlation of 0.37 with the average nonstock momentum strategy. The strong correlation structure among value and momentum strategies across such different assets is interesting since these asset classes have different types of investors, institutional and market structures, and information environments.

Value and momentum are also negatively correlated across asset classes. The correlation between a value strategy in one stock market and a portfolio of momentum strategies in other stock markets is –0.53. In addition, value in one asset class is negatively correlated with momentum in another asset class. For example, the correlation between the average stock value strategy and the average nonstock momentum strategy is –0.26, the correlation between nonstock value strategies and stock momentum strategies is –0.16, and the correlation between nonstock value and nonstock momentum in other asset classes is –0.13 on average. This correlation structure—value being positively correlated across assets, momentum being positively correlated across assets, and value and momentum being negatively correlated within and across asset classes—cannot be explained by the correlation of passive exposure to the asset classes themselves. The value and momentum strategies we examine are long–short and market neutral with respect to each asset class, and yet exhibit stronger correlation across asset classes than do passive exposures to these asset classes.

Panel B of Table II breaks down the correlations of the average stock strategies with each of the nonstock strategies. Nearly all of the value strategies across asset classes are consistently positively correlated, all of the momentum strategies are consistently positively correlated, all of the correlations between value and momentum are consistently negatively correlated, and most of these correlations are statistically different from zero.

For robustness, we also show that defining value differently produces similar negative correlation numbers between value and momentum strategies. Our value measure for equities, *BE/ME*, uses the most recent market value in the denominator, which yields a –0.53 correlation between value and momentum in Table II, Panel A. However, lagging prices by 1 year in the *BE/ME* measure (i.e., using *ME* from 1 year prior) so that the value measure uses price data that do not overlap with the momentum measure, still produces a negative correlation between value and momentum of –0.28, which is highlighted in the Internet Appendix. While these correlations are smaller in magnitude, they are still significantly negative.

In addition, using the negative of the past 5-year return of a stock as a value measure for equities, which is what we use for the nonequity asset classes, also generates negative correlations between value and momentum of similar magnitude (–0.48 as highlighted in the Internet Appendix). This provides more evidence that past 5-year returns capture similar effects as *BE/ME* (Gerakos and Linnainmaa (2012) reach a similar conclusion). Hence, simply using recent prices or using past 5-year returns as a value measure does not appear to be driving the negative correlation between value and momentum returns, which appears to be robust across different value measures.

Figure 1 examines the first principal component of the covariance matrix of the value and momentum returns. The top panel of the figure plots the eigenvector weights associated with the largest eigenvalue from the covariance matrix of the individual stock value and momentum strategies in each stock market. The bottom panel of the figure plots the eigenvector weights for all asset classes, which include a global individual stock value and momentum factor across all countries. Both panels show that the first principal component loads in one direction on all value strategies and loads in exactly the opposite direction on all momentum strategies, highlighting the strong and ubiquitous negative correlation between value and momentum across asset classes as well as the positive correlation among value strategies and among momentum strategies across asset classes. The first principal component, which is essentially long momentum and short value (or vice versa) in every asset class, accounts for 54% of the individual stock strategies' covariance matrix and 23% of the all-asset-class covariance matrix. The commonality among value and momentum strategies across vastly different assets and markets with widely varying information, structures, and investors points to common global factor structure among these phenomena.

The Internet Appendix also shows that correlations across markets and asset classes for the value/momentum combination strategies are lower than they are for value or momentum alone, indicating that the negative correlation between value and momentum offsets some of the common variation when combined together in a portfolio. In other words, it appears that value and momentum load oppositely on some common sources of risk.

Figure 2 illustrates succinctly the return and correlation evidence on value and momentum globally by plotting the cumulative returns to value, momentum, and their combination in each asset market and across all asset markets. The consistent positive returns and strong correlation structure across assets, as well as the negative correlation between value and momentum in every market, is highlighted in the graphs.

III. Relation to Macroeconomic and Liquidity Risk

In this section we investigate possible sources driving the common variation of value and momentum strategies across markets and asset classes.

A. Macroeconomic Risk Exposure

Table III reports results from time-series regressions of value and momentum returns for U.S. stocks, global stocks, nonstock asset classes, and all asset classes combined on various measures of macroeconomic risks.[16]

[16] Chordia and Shivakumar (2002) claim that a conditional forecasting model of macroeconomic risks can explain momentum profits in U.S. stocks, but Griffin, Ji, and Martin (2003) show that neither an unconditional or conditional model of macroeconomic risks can explain momentum

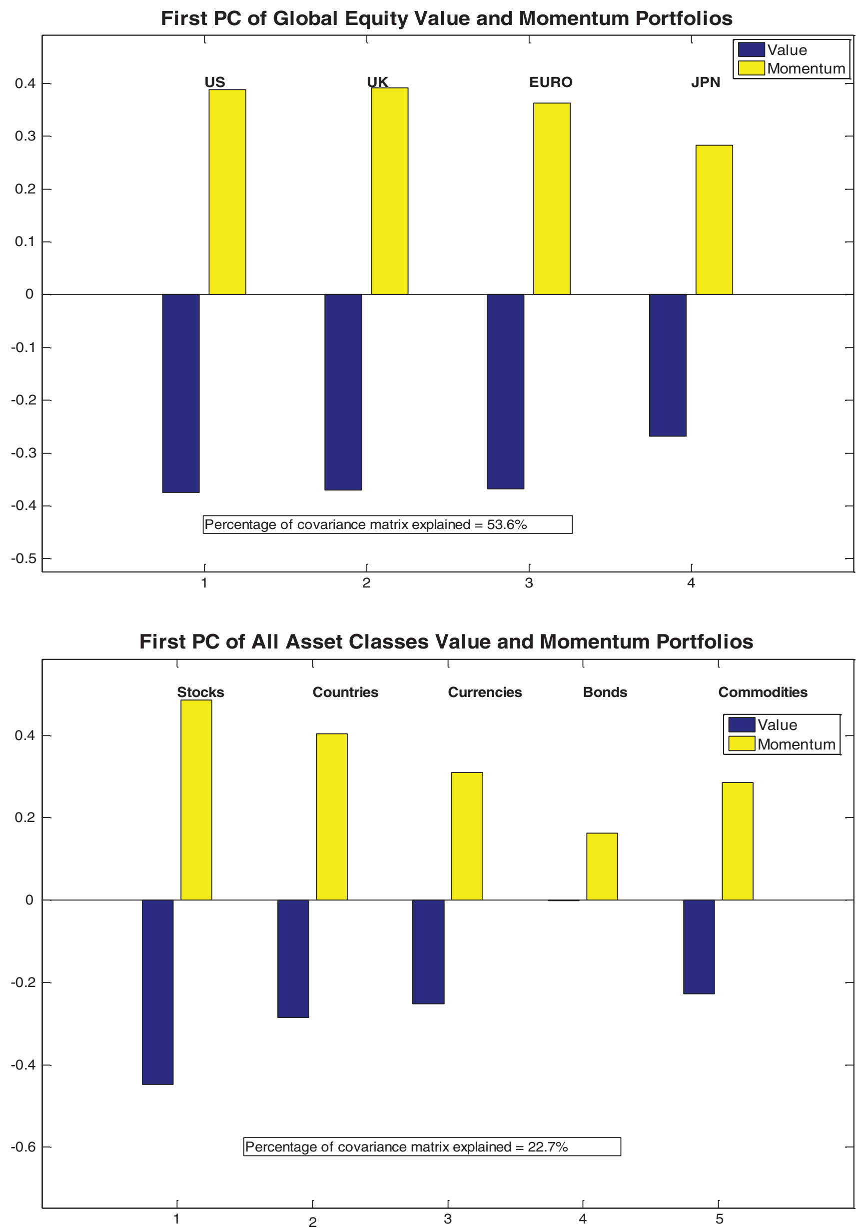

Figure 1. First principal component for value and momentum strategies. Plotted are the eigenvector values associated with the largest eigenvalue of the covariance matrix of returns to value and momentum strategies. The top graph plots the first principal component of value and momentum strategies in individual stocks in four international markets—the United States, the United Kingdom, Europe (excluding the United Kingdom), and Japan—and the bottom graph plots the first principal component for value and momentum strategies in five asset classes—individual stocks globally, country equity index futures, currencies, sovereign bonds, and commodities. Also reported is the percentage of the covariance matrix explained by the first principal component.

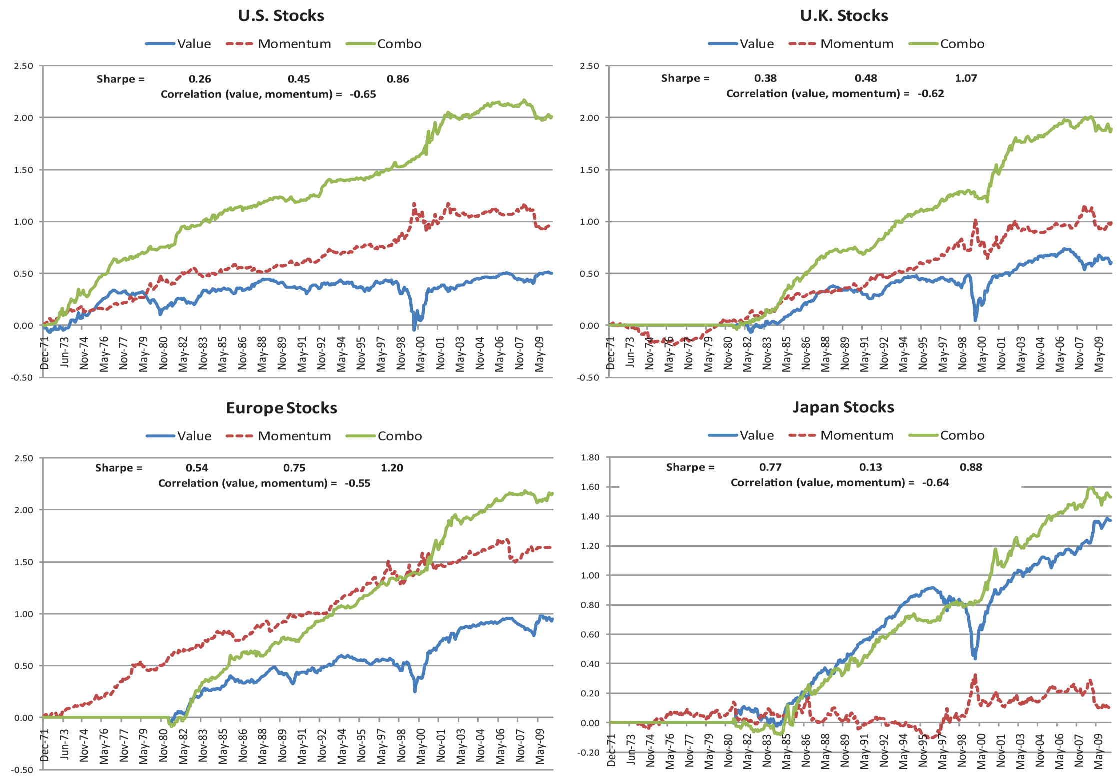

Figure 2. Cumulative returns to value and momentum strategies across markets and asset classes. Plotted are the cumulative (sum of log) returns to value, momentum, and their 50/50 combination strategies in each of the eight asset markets considered: equities in the United States, the United Kingdom, Europe, and Japan; equity index futures; currencies; bonds; and commodities. Returns are plotted for the rank weighted factor portfolios, which are zero-investment portfolios that weight each asset in proportion to its rank based on either value or momentum, following equation (2). Results are also reported for an average of all individual stock strategies across all stock markets ("Global stocks"), across all nonstock asset classes ("Global other asset classes"), and across all markets and asset classes ("Global all asset classes"), where average return series are computed using equal volatility weights across the markets and asset classes to account for differences in volatility across asset classes. All return series are scaled to 10% annual volatility for ease of comparison. Reported on each graph are the annualized Sharpe ratios for each strategy as well as the correlation between value and momentum in each market.

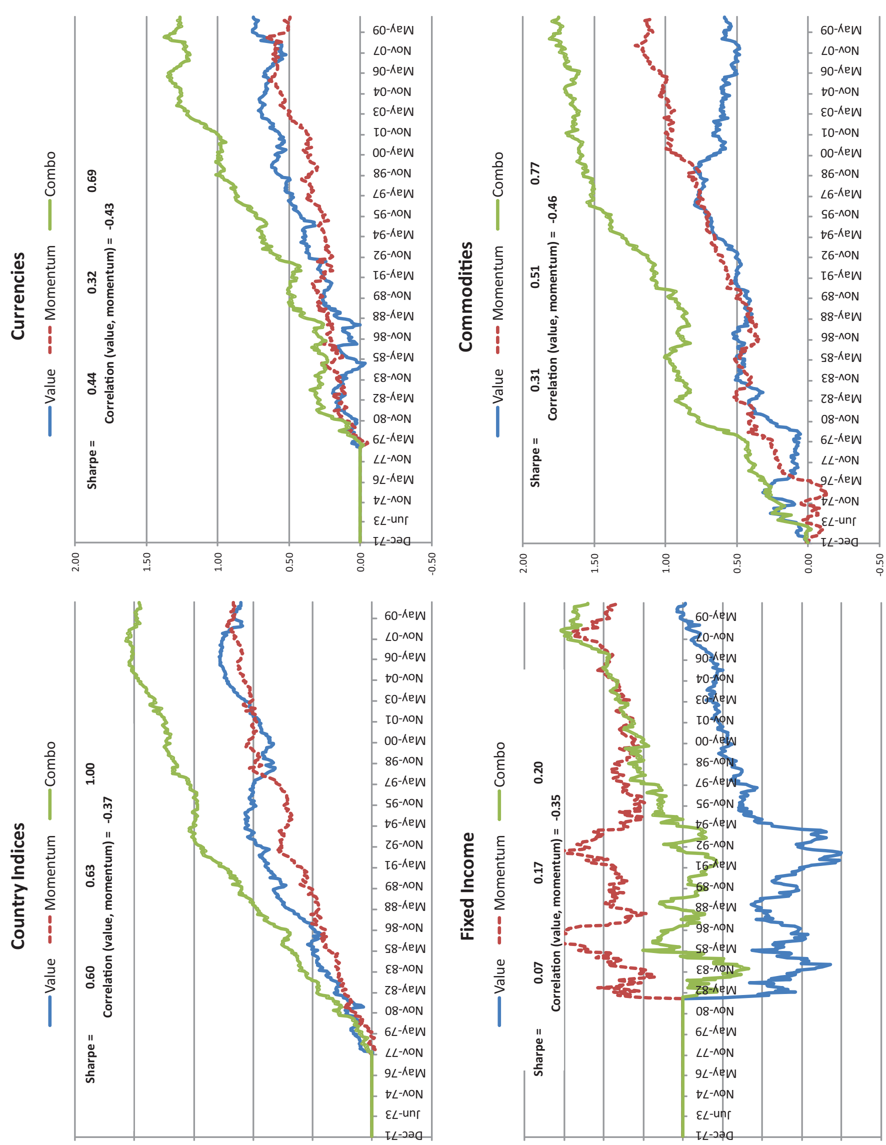

Figure 2. Continued.

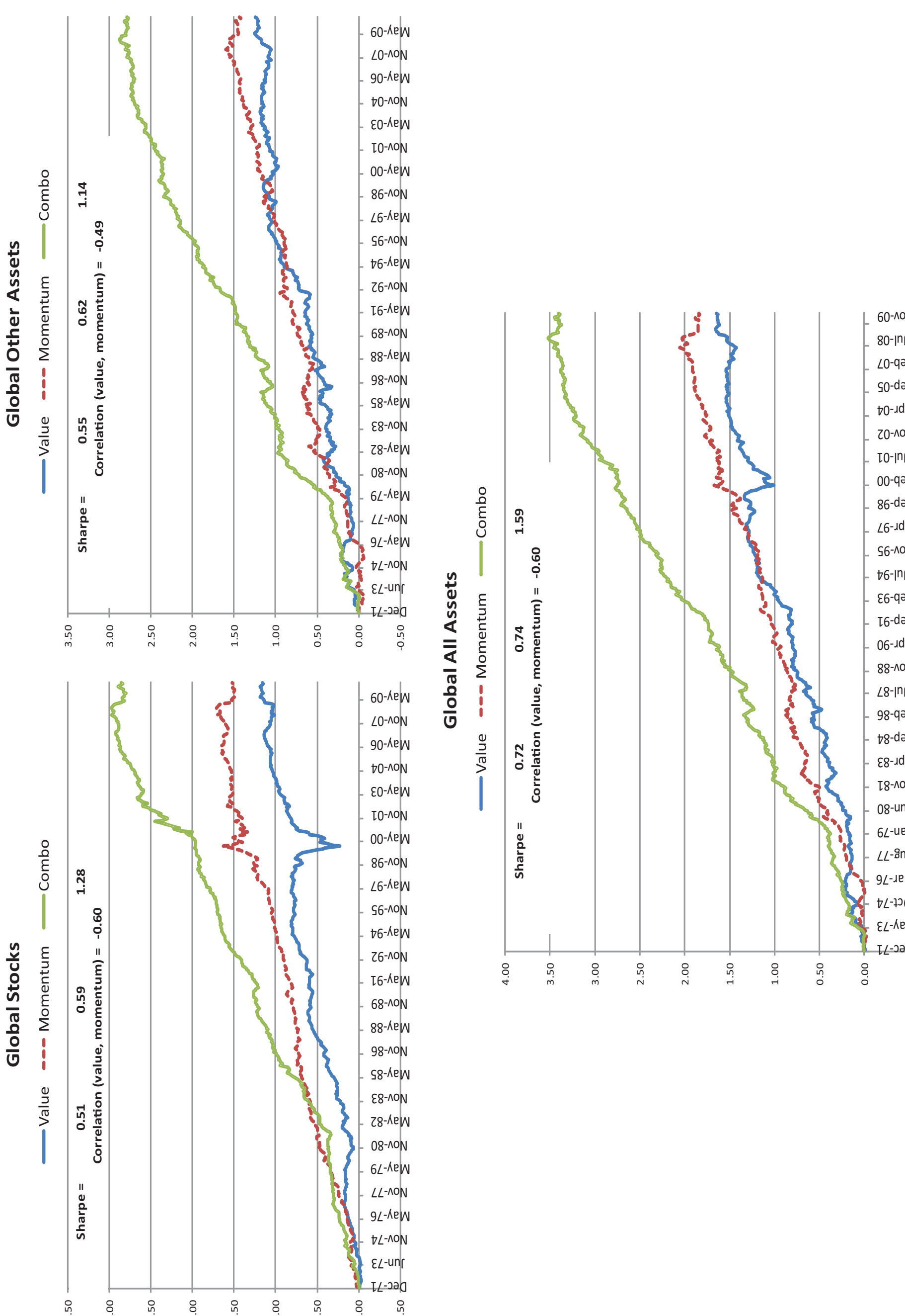

Figure 2. Continued.

The first two columns of Table III report the time series regression coefficients of U.S. value and momentum returns on U.S. macroeconomic variables: long-run consumption growth, a recession indicator, GDP growth, as well as the U.S. stock market return in excess of the T-bill rate and the Fama and French (1993) bond market factor returns TERM and DEF. Consumption growth is the real per capita growth in nondurable and service consumption obtained quarterly and long-run consumption growth is the future 3-year growth rate in consumption, measured as the sum of log quarterly consumption growth 12 quarters ahead as in Parker and Julliard (2005) and Malloy, Moskowitz, and Vissing-Jorgensen (2009). GDP growth is real per capita growth in GDP. These macroeconomic data are obtained from the National Income and Product Accounts (NIPA). The recession indicator is defined using ex post peak (=0) and trough dates (=1) from the NBER.

As Table III shows, U.S. stock value strategies are positively related to long-run consumption growth in U.S. data, consistent with the findings of Parker and Julliard (2005), Bansal and Yaron (2004), Malloy, Moskowitz, and Vissing-Jorgensen (2009), and Hansen, Heaton, and Li (2008). U.S. stock momentum strategy returns are not related to long-run consumption growth. Value and momentum are slightly negatively related to recessions and GDP growth, but none of these relationships are statistically significant. TERM and DEF are positively related to value and the default spread is negatively related to momentum.

The next six columns of Table III report regression results for value and momentum in global stocks, all nonstock asset classes, and all asset classes on global macroeconomic variables. Here, we use global long-run consumption growth, which is a GDP-weighted average of 12-quarter-ahead nondurable and service per capita consumption growth in the United States, the United Kingdom, Europe, and Japan. Global macroeconomic data are obtained from Economic Cycle Research Institute (ECRI), which covers production and consumption data as well as business cycle dates using the same methodology as the NBER for approximately 50 countries over time. Similarly, our global recession variable is the GDP-weighted average of recession indicators in each country and global GDP growth is the average across countries weighted by beginning-of-year GDP. For the market return, we use the MSCI World Index in excess of the U.S. T-bill rate. Finally, since we do not have data to construct TERM and DEF internationally, we use the U.S. versions.

As Table III shows, the global macroeconomic variables are generally not significantly related to value and momentum returns, with a couple of exceptions. Momentum is significantly negatively related to recessions, especially among nonstock asset classes. The default spread is positively related to global stock value, but is insignificantly negatively related to value returns in other

in equities globally across 40 countries, including the United States. We examine the relation between macroeconomic risks and value and momentum strategies globally across asset classes to potentially shed new light on this question.

Table III

Macroeconomic Risk Exposures

Reported are coefficient estimates, t-statistics (in parentheses), and R^2s from time-series regressions of the value and momentum strategy returns in U.S. individual stocks, global individual stocks (across the United States, the United Kingdom, Europe, and Japan), nonstock asset classes, and all asset classes (stock and nonstock) on various measures of macroeconomic risks. The macroeconomic variables are a measure of long-run consumption growth, which is the 3-year future growth rate in per capita nondurable real consumption (quarterly), a recession dummy (0 = peak, 1 = trough) obtained from NBER dates for the United States and ECRI dates outside of the United States, contemporaneous GDP growth rates (from NIPA for the United States and from ECRI outside of the United States), the MSCI world equity index return in excess of the U.S. T-bill rate, and the bond factor returns of Fama and French (1993) TERM and DEF, which represent the term spread on U.S. government bonds and the default spread between U.S. corporate bonds and U.S. Treasuries, respectively. For U.S. stock return regressions, only U.S. macroeconomic variables are used as independent variables. For the global, nonstock, and all-asset-class return regressions, the macroeconomic variables are averaged across all countries, weighting each country in proportion to its GDP. The intercepts from the regressions are not reported for brevity.

		U.S. Stocks			Global Stocks		Nonstock Assets		All Asset Classes	
		Value	Momentum		Value	Momentum	Value	Momentum	Value	Momentum
U.S. values	Long-run	0.0004	0.0001	Global values	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001
for	consumption growth	(2.06)	(0.33)	for	(0.93)	(0.92)	(0.68)	(0.03)	(1.01)	(0.43)
independent	Recession	−0.0068	−0.0056	independent	0.0037	−0.0044	0.0045	−0.0081	0.0043	−0.0072
variables	dummy	(−1.06)	(−0.73)	variables	(0.66)	(−0.75)	(1.48)	(−2.44)	(1.55)	(−2.26)
	GDP growth	−0.0050	0.0019	(GDP-	−0.0011	0.0023	−0.0005	−0.0034	−0.0006	−0.0020
		(−1.75)	(0.57)	weighted)	(−0.39)	(0.80)	(−0.32)	(−2.08)	(−0.45)	(−1.29)
	Market	−0.3435	0.0219		−0.0615	−0.0709	0.0101	−0.0083	−0.0068	−0.0231
		(−7.46)	(0.40)		(−1.41)	(−1.55)	(0.44)	(−0.32)	(−0.32)	(−0.93)
	TERM	0.2038	−0.0234		0.0523	0.0141	−0.0885	0.0370	−0.0551	0.0316
		(2.64)	(−0.25)		(1.04)	(0.27)	(−3.30)	(1.25)	(−2.23)	(1.11)
	DEF	0.7439	−0.7733		0.2650	−0.3752	−0.0510	−0.0787	0.0240	−0.1490
		(5.25)	(−4.57)		(2.86)	(−3.87)	(−1.03)	(−1.44)	(0.53)	(−2.84)
	R-square	13.1%	5.9%		2.3%	6.4%	3.4%	2.9%	2.9%	4.7%

asset classes. DEF is consistently negatively related to momentum returns in all asset classes.

B. Liquidity Risk Exposure

Table IV reports results from regressions that add various liquidity risk proxies to the macroeconomic variables above.

B.1. Measuring Funding and Market Liquidity Risk

To measure liquidity risk exposure, we regress value and momentum returns on shocks to liquidity. We follow Moskowitz and Pedersen (2012) to define our liquidity shocks. We consider both funding liquidity shocks (e.g., Brunnermeier and Pedersen (2009)) and market liquidity shocks. The funding liquidity variables are the Treasury-Eurodollar (TED) spread (the average over the month of the daily local 3-month interbank LIBOR interest rate minus the local 3-month government rate), the LIBOR minus term repo spread (the spread between the local 3-month LIBOR rate and the local term repurchase rate), and the spread between interest rate swaps and local short-term government rates (Swap-T-bill) in each of the four markets. We sign every variable so that it represents liquidity. Hence, we take the negative of the TED spread and the other spreads so that they capture liquidity, since a wider spread represents worse liquidity.

The funding series are available for the common period January 1987 to July 2011. We define shocks to these variables as the residuals from an AR(2) model, following Korajczyk and Sadka (2008) and Moskowitz and Pedersen (2012).[17] The market liquidity variables are the on-the-run minus off-the-run 10-year government Treasury note spread (see Krishnamurthy (2002)) in each of the four markets (the United States, the United Kingdom, Japan, and Europe, using Germany as a proxy); the Pástor and Stambaugh (2003) liquidity measure (their factor, not their factor mimicking portfolio; specifically, their innovations obtained from CRSP); and the illiquidity measure of Acharya and Pedersen (2005), motivated by Amihud's (2002) measure. We construct the Pástor and Stambaugh (2003) and Acharya and Pedersen (2005) measures in other countries by following their methodologies applied to stocks in those markets. Once again, these variables are signed so that they represent *liquidity*, and hence we take the negative of the Acharya and Pedersen (2005) measure, which is based on Amihud's (2002) illiquidity measure.

In addition, we take the first principal component of the correlation matrix of all funding liquidity shocks, all market liquidity shocks, and all liquidity shocks and construct an index of shocks for funding, market, and all liquidity.[18] The principal component of the correlation, rather than covariance, matrix is

[17] There is no special or theoretical reason to use an AR(2). An AR(3), AR(1), and first differences model yield similar results.

[18] A previous version of this paper also included the liquidity measures of Sadka (2006) and Adrian and Shin (2010) and found similar results. However, because the Sadka (2006) and Adrian and Shin (2009) measures require data not available in other equity markets, such as tick and trade

Table IV

Liquidity Risk Exposures

Reported are coefficient estimates and t-statistics (in parentheses) from time-series regressions of the value and momentum strategy returns across all asset classes on a host of liquidity shocks to measure liquidity risk exposure. The liquidity shocks are estimated as residuals from an AR(2) of a set of funding liquidity variables and market liquidity variables. The funding liquidity variables are the Treasury-Eurodollar (TED) spread, the LIBOR minus term repo spread, and the interest rate swap minus T-bill spread. We also compute a principal component weighted average index of the funding liquidity shocks ("Funding liquidity PC") from the correlation matrix of the liquidity shocks and use this as another regressor. The market liquidity variables are the on-the-run minus off-the-run 10-year government Treasury note spread, the Pástor and Stambaugh (2003) liquidity measure, and the illiquidity measure of Acharya and Pedersen (2005). All variables are signed so that they represent liquidity, and hence we take the negative of the Acharya and Pedersen (2005) measure. A principal component-weighted average index of the market liquidity shocks from the correlation matrix of the liquidity shocks is also used. Finally, we use a principal component-weighted average index of all liquidity shocks (funding and market) from the correlation matrix of those liquidity shocks as a regressor, where every variable is signed to represent liquidity. Panel A reports results using only U.S. liquidity risk variables and Panel B reports results using global liquidity risk measures, where the global liquidity risks are estimated by taking the average of all the liquidity measures across countries—the United States, the United Kingdom, Europe, and Japan—weighted by the principal component of each country's contribution to the correlation matrix of each liquidity measure across the four markets. TED spreads, LIBOR—term repo rates, swap—T-bill rates, and on-the-run minus off-the-run spreads for each country are quoted using each country's government bond rates. The Pástor and Stambaugh (2003) and Acharya and Pedersen (2005) measures are computed outside of the United States following the same methodology outlined in those papers to individual stocks in each of the other markets—the United Kingdom, Europe, and Japan. All regressions include the set of macroeconomic variables from Table III as controls (coefficient estimates not reported). The intercepts from the regressions are not reported for brevity.

Panel A: U.S. Liquidity Risk Measures

		Value	Momentum	50/50 Combination	Val – Mom
Funding liquidity risk	TED spread	–0.0052	0.0129	0.0061	–0.0180
		(–1.44)	(3.07)	(2.13)	(–2.62)
	LIBOR-term repo	–0.0137	0.0087	–0.0058	–0.0223
		(–2.15)	(1.11)	(–1.26)	(–1.71)
	Swap-T-bill	–0.0002	0.0141	0.0104	–0.0143
		(–0.05)	(3.34)	(3.67)	(–2.04)
	Funding liquidity PC	–0.0111	0.0153	0.0042	–0.0264
		(–2.89)	(3.31)	(1.49)	(–3.41)
Market liquidity risk	On-the-run – off-the-run	0.0063	–0.0053	–0.0043	0.0115
		(0.53)	(–0.38)	(–0.50)	(0.49)
	Pástor-Stambaugh	0.0034	0.0107	0.0159	–0.0074
		(0.32)	(0.89)	(1.93)	(–0.37)
	Acharya-Pedersen	0.0010	0.0005	0.0013	0.0004
		(2.02)	(1.44)	(3.05)	(0.70)
	Market liquidity PC	–0.0080	0.0222	0.0200	–0.0302
		(–0.44)	(0.94)	(1.06)	(–0.97)
All liquidity risk	All PC	–0.0154	0.0195	0.0043	–0.0349
		(–2.84)	(2.96)	(1.09)	(–3.17)

(*Continued*)

Table IV—*Continued*

Panel B: Global Liquidity Risk Measures

		Value	Momentum	50/50 Combination	Val – Mom
Funding liquidity risk	TED spread	– 0.0067	0.0094	0.0023	– 0.0161
		(– 1.69)	(2.00)	(0.74)	(– 2.05)
	LIBOR-term repo	– 0.0177	0.0139	– 0.0005	– 0.0316
		(– 2.87)	(1.66)	(– 0.08)	(– 2.36)
	Swap-T-bill	– 0.0076	0.0055	– 0.0012	– 0.0131
		(– 2.15)	(1.31)	(– 0.46)	(– 1.86)
	Funding liquidity PC	– 0.0094	0.0112	0.0013	– 0.0206
		(– 4.74)	(3.58)	(0.58)	(– 4.67)
Market liquidity risk	On-the-run – off-the-run	0.0108	– 0.0001	0.0037	0.0109
		(0.68)	(– 0.01)	(0.32)	(0.34)
	Pástor-Stambaugh	0.0010	– 0.0002	0.0003	0.0011
		(1.06)	(– 0.15)	(0.43)	(0.61)
	Acharya-Pedersen	0.0009	0.0008	0.0020	0.0001
		(0.39)	(0.28)	(1.30)	(0.02)
	Market liquidity PC	– 0.0009	0.0016	0.0012	– 0.0025
		(– 0.74)	(1.21)	(1.00)	(– 1.45)
All liquidity risk	All PC	– 0.0079	0.0093	0.0016	– 0.0172
		(– 3.25)	(4.43)	(0.82)	(– 4.63)

used because the liquidity variables have significantly different volatilities and units.

Figure 3 plots the time series of the index of all global liquidity shocks monthly from January 1987 to July 2011. The plot shows that our constructed global liquidity shocks capture a dozen of the largest known liquidity events in global markets over the last 25 years, including the 1987 stock market crash, decimalization, September 11, 2001, the quant meltdown of August 2007, Bear Stearns, and the Lehman Brothers bankruptcy.

B.2. Value and Momentum Returns and Liquidity Risk

Table IV reports regression results of value and momentum returns on the liquidity shocks, controlling for the macro variables in Table III. We only report the coefficient estimates on the liquidity shocks for brevity and because the coefficient estimates on the macro variables do not change much with the addition of the liquidity variables. We examine each liquidity shock in isolation in separate regressions. Panel A of Table IV reports results using the U.S. liquidity shock measures. The dependent variables are the global value and momentum "everywhere" factor returns, the 50/50 combination between them, and the difference between value and momentum returns to test for

data and balance sheet information from prime brokers, we cannot compute them internationally and hence omit them. See Amihud, Mendelson, and Pedersen (1994) for a survey of liquidity and liquidity risk measures.

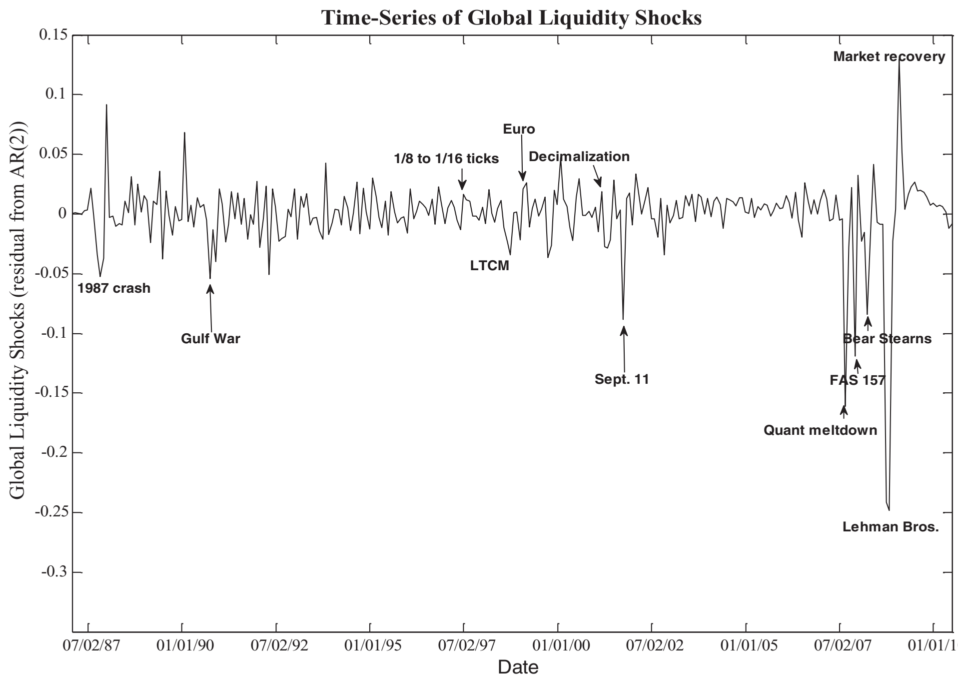

Figure 3. Time series of global liquidity shocks. The time series of global liquidity shocks is plotted from January 1987 to June 2010, where global liquidity shocks are as defined in Section III. Global liquidity shocks are the residuals from an AR(2) of the global liquidity index, which is a principal component weighted average of all market and funding liquidity variables across all markets (the United States, the United Kingdom, Europe, and Japan) as described in Section III. Also highlighted on the graph are episodes known to have generated movements in aggregate liquidity.

differences in liquidity exposure between value and momentum. The first four rows of Panel A of Table IV show that funding liquidity risk is consistently negatively related to value returns and significantly positively related to momentum returns. Value performs poorly when funding liquidity rises, which occurs during times when borrowing is easier, while momentum performs well during these times. The opposite exposure to funding liquidity shocks for value and momentum contributes partly to their negative correlation.[19]

The next four rows examine market liquidity shocks in the U.S. market. Here, we find little relation between market liquidity shocks and value and momentum returns. The Acharya and Pedersen (2005) liquidity measure is marginally

[19] Another interpretation of these funding shocks is that they proxy for changes in risk aversion or risk premia. So, in addition to funding liquidity being tight when spreads are wide, it may also be the case that risk aversion or risk premia in the economy are particularly high. Under this alternative view, however, it would seem that *both* value and momentum returns would decline with rising spreads, whereas we find that value and momentum returns move in opposite directions with respect to these shocks. In addition, the market portfolio and macroeconomic variables are included in the regression, which may partly capture changing risk or risk premia.

negatively related to value and positively related to momentum, but overall the relation between market liquidity shocks and value and momentum returns is weak. Pástor and Stambaugh (2003) (and Sadka (2006)) find a positive and significant relation between U.S. equity momentum returns and their market liquidity shocks. We find the same sign as Pástor and Stambaugh (2003) for our global momentum returns across asset classes over our sample period, but do not detect a significant relation. In addition to our momentum returns covering a wider set of asset classes and a different time period from Pástor and Stambaugh (2003), we also use their factor and *not* their factor mimicking portfolio. They show that the latter exhibits a much stronger relation to momentum, while the former exhibits a weak relation to momentum, consistent with our global results.

Panel B of Table IV reports the regression results using the global funding and market liquidity shocks. Global funding liquidity shocks negatively impact value returns and positively affect momentum returns, but global market liquidity shocks do not seem to have much impact, consistent with the U.S. liquidity measures. Furthermore, the global measures, especially the funding liquidity index, seem to provide more statistical significance. The opposite signed loadings on liquidity risk for value and momentum may partially explain why the two strategies are negatively correlated.

However, the opposite signed loadings on a single factor, such as liquidity risk, cannot explain why *both* value and momentum earn positive risk premia. On the one hand, part of the returns to momentum can be explained as compensation for liquidity risk exposure since momentum loads positively on liquidity shocks and liquidity risk carries a positive risk premium. On the other hand, value loads negatively on liquidity risk, which makes its positive return an even deeper puzzle.

Why does momentum load positively and value load negatively on liquidity risk? One simple and intuitive story might be that momentum captures the most popular trades, being long the assets whose prices have recently appreciated as fickle investors flocked to these assets. Value, on the other hand, expresses a contrarian view, where assets have experienced price declines over several years. When a liquidity shock occurs, investor liquidations (from cash needs, redemptions, risk management, "running for the exit" at the same time; see Pedersen (2009)) puts more price pressure on the more "crowded" trades. These liquidations may affect crowded high momentum securities more than the less popular contrarian/value securities. Further investigation into the opposite signed exposure of value and momentum to liquidity risk is an interesting research question, but beyond the scope of this paper.

Finally, as Table IV shows, because of the opposite signed exposure of value and momentum to funding liquidity shocks, the 50/50 equal combination of value and momentum is essentially immune to funding shocks, and yet, as we have shown, generates huge positive returns. Thus, while exploring liquidity risk's relation to value and momentum more deeply may be interesting, liquidity risk by itself cannot explain why a combination of value and momentum is

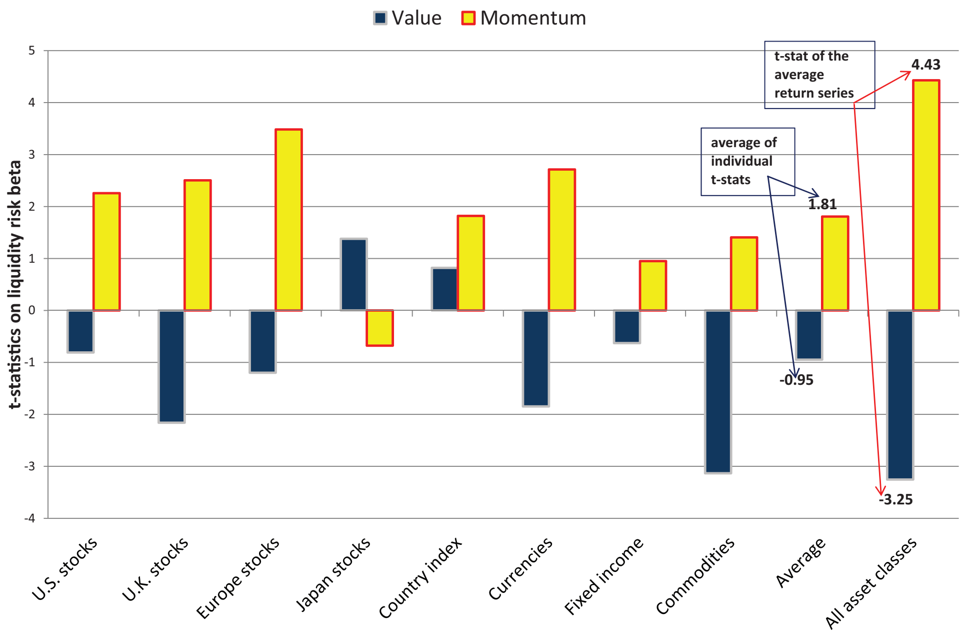

Figure 4. Liquidity risk beta *t*-statistics. Plotted are the *t*-statistics of the liquidity risk beta estimates of value and momentum strategies in each asset class using shocks to the global liquidity index as described in Section III. Also reported is the cross-sectional average *t*-statistic of value and momentum strategies across the asset classes ("average") as well as the *t*-statistic of the average return series across all asset classes for value and momentum ("all asset classes").

so profitable, and hence can only partially explain part of the cross-sectional variation in returns.

B.3. The Power of Averaging Across Markets

A key feature of the analysis in Tables III and IV is that we examine the average returns to value and momentum across a wide set of markets and asset classes simultaneously. The power of looking at the universal average return to value and momentum greatly improves our ability to identify common factor exposure. For example, if we examine each individual value and momentum strategy's exposure to liquidity risk separately, we do not find nearly as strong a pattern and, in fact, might conclude there exists little evidence of any reliable relation to liquidity risk.

Figure 4 depicts the *t*-statistics of the liquidity betas of each of our individual market and asset class value and momentum strategies. The average *t*-statistic of the liquidity betas for value is –0.95 and for momentum is 1.81—hardly convincing. In contrast, when we regress the average value and momentum return series across all markets and asset classes on global liquidity shocks, we get a *t*-statistic for the liquidity beta of –3.25 for value and 4.43 for momentum. The average liquidity beta among the individual strategies is not nearly as strong as the liquidity beta of the average. Averaging across all markets and asset classes mitigates much of the noise not related to value or momentum, such as idiosyncratic regional or asset-specific noise, allowing for better identification of a common factor such as liquidity risk to emerge. When we restrict attention to one asset class at a time, or to one strategy within an asset class, the patterns above are difficult to detect. The scope and uniformity of studying value and momentum everywhere at once is what allows these patterns to be identified.

IV. Comovement and Asset Pricing Tests

The strong common factor structure evidenced in Section II and the link to liquidity risk in Section III suggest that we formally examine asset pricing tests to assess the economic significance of these patterns and how much of the return premia to value and momentum can be captured by this common variation.

A. Explaining Value/Momentum in One Market with Value/Momentum in Other Markets

We first examine how well value and momentum in one market or asset class are explained by value and momentum returns in other asset classes. This test is not a formal asset pricing test, but a test of comovement across markets and asset classes. In the next subsection, we examine formal asset pricing tests. Specifically, we run the regression

$$R^p_{i,t} - r_{f,t} = \alpha^p_i + \beta^p_i MKT_t + v^p_i \sum_{j\neq i} w_j VAL_{j,t} + m^p_i \sum_{j\neq i} w_j MOM_{j,t} + \varepsilon^p_{i,t}, \quad (4)$$

where $R^p_{i,t}$ is the time t return to portfolio p among the six high, middle, and low value and momentum portfolios in one of the eight asset markets i, for a total of 48 test assets. The time series of excess returns (in excess of the U.S. T-bill rate) of each portfolio is regressed on the excess returns of the market portfolio MKT (proxied by the MSCI World Index) and the returns to value and momentum factors in *all other* markets and asset classes. The latter two variables are constructed as the equal volatility-weighted average of the zero-cost signal-weighted value and momentum factors in all other markets (where w_j represents the equal volatility weight for each asset class), excluding the market whose test assets are being used as the dependent variable.

We estimate equation (4) for each market and asset class separately. Figure 5 plots the actual average return of each of the test assets against the predicted expected return from the regression. The plot shows how much of the average returns to value and momentum portfolios in one market or asset class can be explained by value and momentum returns from other markets and asset classes. A 45° line passing through the origin is also plotted to highlight both the cross-sectional fit and the magnitude of the pricing errors across test assets.

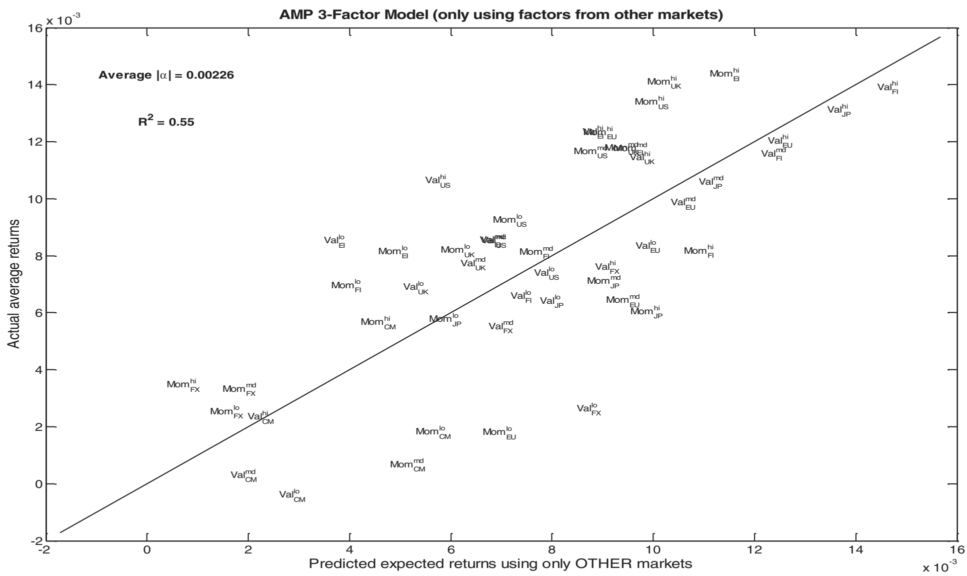

Figure 5. Explaining value and momentum in one market with value and momentum in other markets. Plotted are the actual average returns (in excess of the U.S. 1-month T-bill rate) of the 48 value and momentum low, middle, and high portfolios in each market and asset class against their predicted expected returns using their betas with respect to value and momentum strategies in all other markets globally. Specifically, for each of the eight markets we consider (U.S. stocks, U.K. stocks, Europe stocks, Japan stocks, country index futures, currencies, government bonds, commodities) we estimate the betas of value and momentum low, middle, and high portfolios in each market with respect to a value and momentum factor across all other markets by running a time-series regression of each value and momentum portfolio in one market on the (equal volatility-weighted) average of the value and momentum factors across all other markets, excluding the market being analyzed. The predicted value from this regression is the predicted expected return of the strategy that we plot against the average actual average return over the sample period. The average absolute value of the alphas from these regressions and the cross-sectional R^2 of the actual average returns against the predicted expected returns are also reported. To highlight both the alphas and cross-sectional fit, a 45° line is plotted through the origin.

As Figure 5 shows, the average returns line up well with the predicted expected returns. The cross-sectional R^2 is 0.55 and the average absolute value of the pricing errors (alpha) is 22.6 basis points per month. A formal statistical test of the joint significance of the pricing errors is not possible since the independent variables change across test assets for each market and asset class (which is why this is not a formal asset pricing test).

The results indicate that value and momentum returns in one market are strongly related to value and momentum returns in other markets and asset classes. Unlike many asset pricing tests conducted in a single market, here there is no overlap of securities between the test assets used as the dependent variable and the factors used as regressors. The dependent variable contains securities from a completely separate market or asset class from those used to construct the factors on the right-hand side of the regression. Hence, the evidence in Figure 5 makes a compelling case for common global factor structure in value and momentum returns and suggests that this common variation is economically meaningful since it captures a significant fraction of the cross section of average returns.

B. A Global Three-Factor Model

To conduct a more formal asset pricing test, and to compare across various asset pricing models, we construct a three-factor model similar to equation (4), but where the regressors are the same for every asset. This three-factor model is similar in spirit to those of Fama and French (1993) and Carhart (1997), but applied globally to all markets and asset classes we study. Specifically, we estimate the following time-series regression for each of the 48 high, middle, and low value and momentum portfolios across asset classes:

$$R^p_{i,t} - r_{f,t} = \alpha^p_i + \beta^p_i MKT_t + v^p_i VAL^{everywhere}_t + m^p_i MOM^{everywhere}_t + \varepsilon^p_{i,t}, \tag{5}$$

where $VAL^{everywhere}_t$ and $MOM^{everywhere}_t$ are the equal-volatility-weighted across-asset-class value and momentum factors.

The first graph in Panel A of Figure 6 plots the actual sample average returns of the 48 test assets versus their predicted expected returns from equation (5) along with a 45° line through the origin to highlight the magnitude of the pricing errors. The cross-sectional R^2 is 0.71 and the average absolute value of the alpha is 18 basis points, indicating slightly better fit than equation (4), which is not surprising, since, unlike equation (4), equation (5) contains some of the same securities on the left- and right-hand side of the regression. However, the fit is similar to equation (4), and equation (5) also allows for a formal joint test of the significance of the alphas, since the explanatory variables are the same for each test asset. Hence, we report the Gibbons, Ross, and Shanken (GRS, 1989) F-statistic and p-value for a joint test of the pricing errors.

The remaining graphs in Panel A of Figure 6 plot the pricing errors of the 48 test assets under alternative asset pricing models: the global CAPM, using the MSCI World Index as the market proxy; a four-factor model inspired by Carhart (1997), which is the Fama–French three-factor model consisting of the U.S. stock market *RMRF*, the U.S. size factor *SMB*, and the U.S. value factor *HML* augmented with the U.S. stock momentum factor *UMD* obtained from Ken French's website, that we refer to as the "Fama–French four-factor model"; and a six-factor model that adds the Fama and French (1993) bond return factors *DEF* and *TERM*, which capture the default and term spread for U.S. bonds, that we refer to as the "Fama–French six-factor model." As Figure 6 shows, the global CAPM does not do a very good job fitting the cross section of value and momentum returns across markets and asset classes, producing the largest absolute pricing errors and smallest R^2. The Fama–French four- and six-factor specifications explain the returns a little better than the CAPM, but not nearly as well as the global three-factor model. The Fama–French factors

Panel A: 48 Value and Momentum Portfolios across Markets and Asset Classes

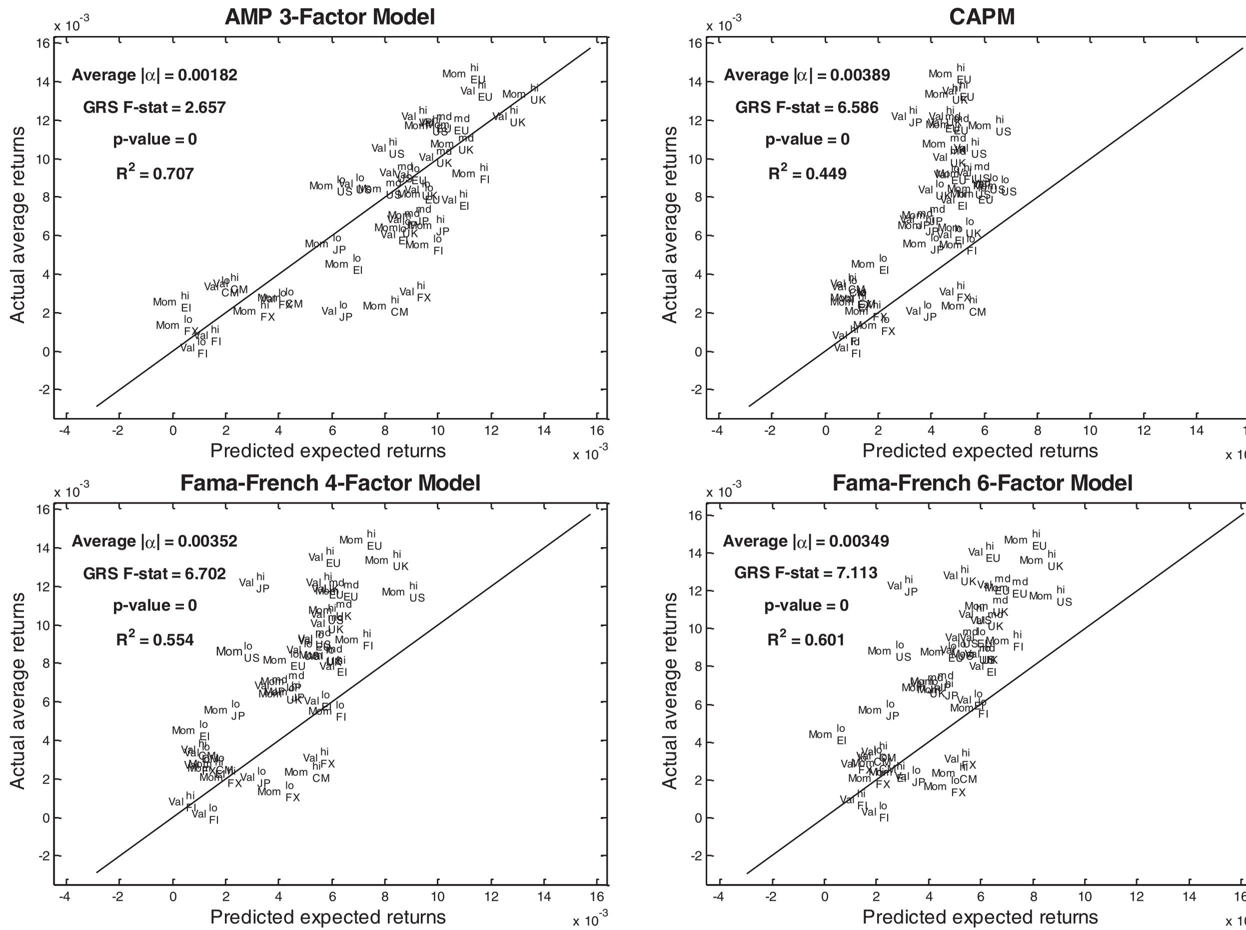

Figure 6. Asset pricing tests of the cross section of expected returns. Plotted are the actual average returns versus model-implied expected returns of the 48 value and momentum low, middle, and high portfolios in each market and asset class under the global CAPM (MSCI World Index), Fama and French four-factor model consisting of

Panel B: Fama-French 25 Size-Value and 25 Size-Momentum Portfolios (U.S. Stocks)

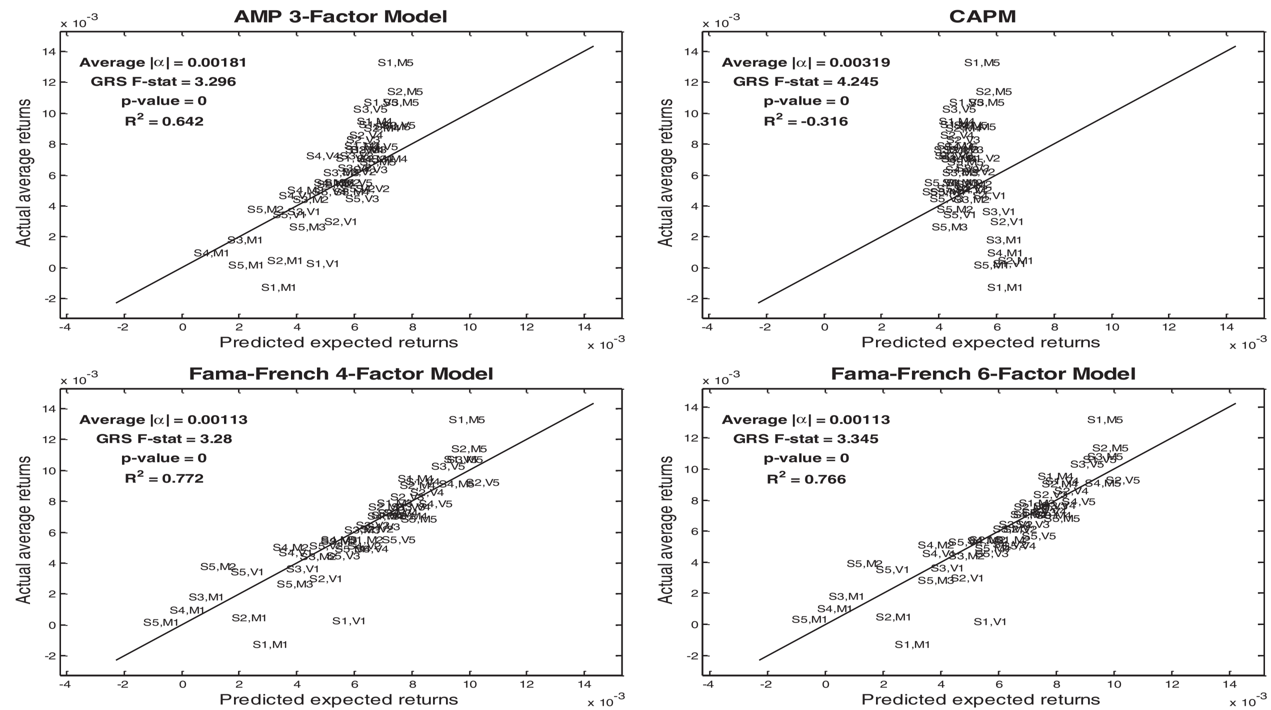

Figure 6. Continued.
U.S. market, size, value, and momentum factors (RMRF, SMB, HML, and UMD), Fama and French six-factor model that adds TERM and DEF to the four-factor model to capture term and default risk premia, and the AMP three-factor model consisting of a global market factor (MSCI World Index), a value everywhere factor, and a momentum everywhere factor, which are value and momentum long-short portfolios diversified across the eight asset classes we consider, where each asset class is weighted by the inverse of its in-sample volatility. A 45° line that passes through the origin is added to highlight the pricing errors (vertical distances to the 45° line), where each model is forced to also price the equity premium. Also reported on each graph are the average absolute value of the alphas, the F-statistic and p-value from the GRS test, and the cross-sectional R^2 under each asset pricing model.

generate twice the absolute magnitude of pricing errors as the three-factor global model and have much lower R^2s.

Panel B of Figure 6 repeats the same plots for test assets derived only from U.S. stocks. Here, we use the Fama–French 25 size-value and 25 size-momentum portfolios from Ken French's website (http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html) as test assets. These are, respectively, 5×5 double-sorted portfolios of U.S. stocks based on size and *BE/ME* and 5×5 portfolios sorted on size and past 2- to 12-month returns. Our three-factor model derived from other markets and asset classes does a reasonable job explaining the returns to these 50 U.S. equity portfolios. The cross-sectional R^2 is 0.64 and the average absolute pricing error is only 18 basis points. While the Fama–French factors, which are derived from the same U.S. stocks as the test assets, obviously do slightly better, our three-factor model, which is derived from other asset classes, captures a significant fraction of the cross-sectional variation in U.S. equity returns. In addition, our three-factor model does not contain a size factor, which is important for pricing the Fama-French U.S. stock portfolios. If we exclude the two smallest quintiles of stocks from the Fama-French portfolios, then our three-factor model does as well as the Fama-French model in pricing the remaining Fama-French U.S. portfolios.

Taken together, Panel A of Figure 6 shows that our global three-factor model can explain the returns to value and momentum across markets and asset classes much better than local U.S. factors can and Panel B shows that our global factors can explain the local returns to value and momentum in U.S. stocks almost as well as the U.S. factors can. These results suggest that global value and momentum portfolios across markets and asset classes are closer to the efficient frontier than U.S. stock-only value and momentum portfolios, and therefore provide a more robust set of asset pricing factors that can be used more broadly.

C. Further Pricing Tests and Economic Magnitudes

To further investigate the economic importance of the commonality among value and momentum strategies across asset markets, we examine their relation to macroeconomic and liquidity risks through cross-sectional and time-series asset pricing tests.

C.1. Cross-Sectional Pricing Tests

Table V reports Fama–MacBeth cross-sectional regressions of returns of the 48 value and momentum test portfolios on their betas with respect to funding liquidity risk, GDP growth, long-run consumption growth, TERM, and DEF. Regressions are run in the style of Fama and MacBeth (1973), where the cross section of monthly returns are regressed on the betas (estimated univariately using rolling windows of the past 60 months of returns) each month, and the time-series mean and *t*-statistic of the cross-sectional regression coefficients are reported in Table V. As the first row of Table V shows, liquidity risk betas

Table V

Cross-Sectional Asset Pricing Tests of Global Value and Momentum Strategies

Reported are Fama and MacBeth (1973) regression coefficient estimates and t-statistics of the cross section of average returns to the 48 value and momentum portfolios across the eight markets and asset classes we consider. The dependent variable is the cross section of returns on the low, middle, and high value and momentum portfolios of individual stocks in the United States, the United Kingdom, Europe, Japan, country index futures, currencies, government bonds, and commodities. The regressors are beta estimates of these portfolios with respect to the "All" liquidity risk measure from Table IV (the principal component-weighted average index of all liquidity shock measures across all markets globally); GDP growth; long-run consumption growth; the MSCI world index ("market"); the value everywhere factor, consisting of an equal volatility-weighted average of value strategies across all markets and asset classes; and a momentum everywhere factor defined similarly. The last four rows report results using only funding and market liquidity variables to measure liquidity risk, where the principal component-weighted average index of funding and market liquidity shocks are used separately to measure funding liquidity risk and market liquidity risk. Betas are estimated in a univariate regression with respect to each of the factors using a rolling window of the past 60 months of returns. For the market, a Dimson correction is used to account for possible nonsynchronous trading effects, where each portfolio's returns are estimated on the contemporaneous value of the market plus 2 month lags of market realizations and the beta is the sum of the three coefficients on the contemporaneous and 1- and 2-month lags of the market. The cross-sectional regressions are estimated in the style of Fama and MacBeth (1973), where the cross section of returns on the 48 portfolios are regressed each month on the cross-section of beta estimates and the time-series mean and t-statistics of the monthly regression coefficients are reported.

Fama–MacBeth Cross-Sectional Regressions							
$\beta_{Liquidity\ risk}$	$\beta_{GDP\ growth}$	β_{LRCG}	β_{TERM}	β_{DEF}	β_{Mkt}	β_{Value}	$\beta_{Momentum}$
Dependent variable: Cross-section of 48 value and momentum portfolios							
0.0024							
(3.05)							
	0.0003	0.0005	0.0021	0.0023			
	(0.43)	(0.42)	(2.19)	(2.18)			
0.0023	−0.0001	0.0012	0.0014	0.0001			
(2.29)	(−0.13)	(1.01)	(1.59)	(0.11)			
0.0005			0.0015	0.0020	0.0029		
(0.56)			(1.75)	(2.22)	(2.58)		
0.0016	0.0018	−0.0001	0.0033	0.0014	−0.0006	0.0031	0.003
(1.38)	(2.87)	(−0.03)	(2.87)	(1.12)	(−0.38)	(3.96)	(3.53)
Funding liquidity variables only							
0.0022	−0.0002	0.0019	0.0011	0.0015			
(2.06)	(−0.30)	(1.45)	(1.05)	(1.30)			
0.0012	0.0019	0.0003	0.0027	0.0011	0.0008	0.0034	0.0031
(1.80)	(3.28)	(0.17)	(2.19)	(0.84)	(0.58)	(4.40)	(3.50)
Market liquidity variables only							
0.0001	0.0003	0.0005	0.0021	0.0022			
(0.07)	(0.48)	(0.44)	(2.67)	(2.63)			
−0.0013	0.0019	−0.0010	0.0045	0.0030	0.0004	0.0038	0.0040
(−0.88)	(3.19)	(−0.77)	(5.05)	(2.73)	(0.31)	(5.94)	(5.82)

capture part of the cross-sectional variation in average returns across the 48 portfolios, as indicated by the positive and significant coefficient on the liquidity beta. That coefficient also represents the risk premium for liquidity risk among the 48 test assets, which is 24 basis points per month or about 3% per year. The Fama–MacBeth regressions not only test the cross-sectional relation between average returns and betas with respect to a factor, but the time series of the coefficient estimates represents the return series to a minimum variance portfolio with a unit exposure to that factor (see Fama and MacBeth (1973) and Fama (1976)). Hence, the time series of monthly coefficient estimates represents a factor mimicking portfolio for liquidity risk, which we call $FP_{liq\ risk}$. Likewise, the coefficients on the other variable represent the returns to factor-mimicking portfolios for those factors, each orthogonalized to the other facotrs, which we will use in time-series asset-pricing tests to follow.

The second row of Table V shows that neither GDP growth nor long-run consumption growth captures much cross-sectional variation in returns, but TERM and DEF do, exhibiting a risk premium of 21 and 23 basis points, respectively. However, the third row of Table V adds liquidity betas to the regression, where we find that the significance of TERM and DEF are subsumed by liquidity risk. Finally, we add betas with respect to the global three-factor model—the MSCI World Index, and the value and momentum everywhere factors. It is perhaps not too surprising that betas with respect to value and momentum factors capture average returns to value and momentum portfolios and that they subsume a significant portion of the explanatory power of other factors such as liquidity risk.

The next two rows of regression results in Table V repeat the regressions using only funding liquidity variables to capture liquidity risk and the last two rows use only market liquidity variables to measure liquidity risk. As Table V shows, only funding liquidity risk appears to be priced in the cross section of our global assets, and exposure to value and momentum common factors seems to capture part of funding liquidity risk exposure.

C.2. Time-Series Pricing Tests

To gain more insight into the economic magnitudes that liquidity risk and the other factors explain, we use the factor mimicking portfolios created from the Fama–MacBeth regressions to conduct time-series asset pricing tests. Specifically, we regress each of the 48 portfolios' time series of monthly returns on the factor mimicking portfolio returns for liquidity risk, GDP growth, and long-run consumption growth, as well as TERM, DEF, and the value and momentum everywhere factors. Because we use factor mimicking portfolios as regressors, both the dependent and independent variables are measured in returns, and hence we can conduct formal pricing tests.

Panel A of Table VI reports the results for the 48 value and momentum portfolios across markets and asset classes. We also include the market portfolio in every regression. For each factor model, we report the GRS F-statistic and p-value for testing the joint significance of the alphas under each model. We also

Table VI

Time-Series Asset Pricing Tests of Global Value and Momentum Strategies

Panel A reports results from time-series asset pricing tests of the 48 value and momentum portfolios across markets and asset classes on a set of global and U.S.-only asset pricing models. The global models include a global CAPM (MSCI World index); a two-factor model of the global market portfolio plus a factor-mimicking portfolio for a global liquidity risk factor (estimated from the cross-sectional regression coefficients in Table IV); a six-factor model that includes the global market and factor-mimicking portfolios for global liquidity risk, GDP growth, long-run consumption growth (each estimated from the cross-sectional regression coefficients in Table IV), and TERM and DEF; the three-factor AMP model of the global market plus all-asset-class value and momentum factors, as well as two-factor versions that include the market and just one of either all-asset-class value or momentum. The U.S.-only factor models include the U.S. CAPM (U.S. CRSP value-weighted index), Fama and French three-factor model that adds size and value factors to the market, Fama–French four-factor model that adds a momentum factor, and Fama–French six-factor model that adds TERM and DEF as additional factors. Panel B reports results for time-series tests using the same asset pricing models on the 25 Fama–French size and *BE/ME* portfolios and 25 size and momentum portfolios that pertain only to U.S. individual stocks. Panel C reports results for 13 hedge fund indices obtained from DJCS and HFRI. All panels report the GRS (1989) F-statistic on the joint significance of the alphas under each model from the time-series regressions, the p-value of the F-statistic, the average absolute alpha, the average time-series R^2, the cross-sectional R^2 of average returns on the predicted expected return from each model, and the percentage of the covariance matrix captured by each model using the *Eig%* metric of Moskowitz (2003) and described in Section IV. Regressions are estimated from monthly returns.

	Asset Pricing Models	GRS F-Stat	p-Value	Average $\lvert\alpha\rvert$	Average Time-Series R^2	Cross-Sectional R^2	% of Covariances
Panel A: 48 Value and Momentum Portfolios Globally across Asset Classes							
Global Asset Pricing Factors	Mkt (Global CAPM)	6.02	0.000	0.0035	0.40	0.52	57%
	Mkt, $FP_{\text{liq risk}}$	5.02	0.000	0.0031	0.48	0.54	64%
	Mkt, $FP_{\text{liq risk}}$, FP_{GDPg}, FP_{LRCG}, TERM, DEF	4.09	0.000	0.0027	0.59	0.56	80%
	Mkt, $VAL_{\text{everywhere}}$, $MOM_{\text{everywhere}}$	2.66	0.000	0.0018	0.68	0.72	74%
	Mkt, $VAL_{\text{everywhere}}$	3.72	0.000	0.0028	0.42	0.43	68%
	Mkt, $MOM_{\text{everywhere}}$	3.80	0.000	0.0022	0.42	0.57	70%
U.S. Asset Pricing Factors	Mkt (U.S. CAPM)	6.59	0.000	0.0039	0.30	0.44	47%
	FF 3-Factor	7.18	0.000	0.0036	0.31	0.50	53%
	FF 4-Factor	6.70	0.000	0.0035	0.33	0.55	63%
	FF 6-factor	7.11	0.000	0.0035	0.39	0.62	64%

(*Continued*)

Table VI—*Continued*

	Asset Pricing Models	GRS F-Stat	p-Value	Average $\lvert\alpha\rvert$	Average Time-Series R^2	Cross-Sectional R^2	% of Covariances
	Panel B: Fama–French 25 Size-Value and 25 Size-Momentum Portfolios						
Global Asset Pricing Factors	Mkt (Global CAPM)	4.09	0.000	0.0030	0.41	0.20	48%
	Mkt, $FP_{liq\ risk}$	4.12	0.000	0.0030	0.42	0.20	49%
	Mkt, $FP_{liq\ risk}$, FP_{GDPg}, FP_{LRCG}, TERM, DEF	4.76	0.000	0.0035	0.57	0.38	61%
	Mkt, $VAL_{everywhere}$, $MOM_{everywhere}$	3.22	0.000	0.0019	0.70	0.68	66%
U.S. Asset Pricing Factors	Mkt (U.S. CAPM)	4.25	0.000	0.0032	0.73	0.17	82%
	FF 3-Factor	3.81	0.000	0.0023	0.87	0.30	93%
	FF 4-Factor	3.28	0.000	0.0011	0.91	0.77	97%
	FF 6-factor	3.35	0.000	0.0011	0.91	0.77	97%
	Panel C: 13 Hedge Fund Indexes						
Global Asset Pricing Factors	Mkt (Global CAPM)	12.14	0.000	0.0032	0.30	0.20	43%
	Mkt, $FP_{liq\ risk}$	12.36	0.000	0.0025	0.34	0.30	47%
	Mkt, $FP_{liq\ risk}$, FP_{GDPg}, FP_{LRCG}, TERM, DEF	11.86	0.000	0.0022	0.46	0.17	53%
	Mkt, $VAL_{everywhere}$, $MOM_{everywhere}$	7.26	0.000	0.0018	0.41	0.47	54%
U.S. Asset Pricing Factors	Mkt (U.S. CAPM)	12.14	0.000	0.0028	0.30	0.18	43%
	FF 3-Factor	12.64	0.000	0.0026	0.35	0.19	47%
	FF 4-Factor	13.03	0.000	0.0022	0.37	0.36	49%
	FF 6-factor	12.25	0.000	0.0021	0.44	0.36	51%

report the average absolute value of the alphas to gauge the magnitude of the pricing errors under each model, the cross-sectional R^2 of the average returns on the test assets against the predicted expected returns from each model, and the *Eig%* metric from Moskowitz (2003), which is the sum of eigenvalues from the covariance matrix of the test assets implied by the model divided by the sum of eigenvalues of the sample covariance matrix. The *Eig%* measure captures how much of the covariance matrix of returns among the test assets each model can explain.

As the first row of Panel A of Table VI shows, the market portfolio alone (global CAPM) generates substantial pricing errors—an average absolute alpha of 35 basis points per month that is easily rejected by the GRS test—and leaves a lot of time-series and cross-sectional variation unexplained. The market portfolio captures about 57% of the covariation among the returns. The second row adds the liquidity risk factor mimicking portfolio as a regressor, and although the GRS test is still rejected, the average absolute alpha declines to 31 basis points, the cross-sectional R^2 increases, and the amount of covariation captured increases. Hence, liquidity risk adds some additional explanatory power for both pricing and common variation of value and momentum portfolios globally across asset classes.

While there is a link between value and momentum and liquidity risk, only a small fraction of the return premia and covariation is captured by our proxies for these risks. We view these findings as an important starting point for possible theories related to value and momentum phenomena, but emphasize that we are far from a full explanation of these effects. We also recognize that measurement error in liquidity risk may limit what we can explain. In addition, a single liquidity risk factor alone cannot explain value and momentum since they are negatively correlated with each other but both produce positive returns, unless there is substantial time variation in liquidity risk betas and in the liquidity risk premium. Thus, it is not surprising that the pricing errors from this model specification remain large.

The third row of Table VI, Panel A adds factor mimicking portfolio returns for GDP growth, long-run consumption growth, and TERM and DEF. Pricing errors decline further while R^2s and the amount of covariation explained increase. The fourth row uses our three-factor model, which provides the best fit. Here, the average absolute alpha is only 18 basis points, the cross-sectional R^2 is 72%, and 84% of the covariation among the test assets is captured by these factors. The next two rows further show that having both value and momentum in the model is important, since having only value or momentum by itself increases pricing errors and decreases the fit considerably. This further underscores the difficulty of using a single factor to explain both value and momentum.

The last four rows of Table VI, Panel A examine models of U.S. stock factors: the U.S. market portfolio in excess of the U.S. T-bill rate, the Fama–French three-factor model, the Fama–French four-factor model that adds the momentum factor, and the Fama–French six-factor model that also adds TERM and DEF. As Table VI shows, the U.S. factors do not do a great job of describing the global value and momentum portfolio returns, leaving larger pricing errors and lower R^2s, and capturing a smaller fraction of their covariance matrix.

Panel B of Table VI repeats the same exercise as Panel A, but uses the 25-size-*BE*/*ME* and 25 size-momentum U.S. equity portfolios from Ken French's website as test assets. Not surprisingly, the Fama–French U.S. factors do a good job of capturing these returns, though the GRS test is still rejected. However, the global value and momentum everywhere factors, which consist primarily of non-U.S. equities and other asset classes, also do a good job explaining the 50 U.S. equity-based test assets—the average absolute alpha is only 19 basis points, the cross-sectional R^2 is 68%, and the percentage of covariation captured is 66%. This is better than the Fama–French three factor model does and only slightly worse than the Fama–French four- or six-factor models, which are specifically designed to capture these portfolios and are constructed from the same set of securities as the test assets themselves.

Finally, Panel C of Table VI considers how well these factor models can explain hedge fund returns. Using the returns of 13 hedge fund indices from Dow Jones Credit Suisse (DJCS) and Hedge Fund Research Institute (HFRI) that include from DJCS the Market Neutral, Long-Short, Multi Strategy, Macro, Managed Futures, Currency, Emerging Markets, and Overall hedge fund indices and from HFRI the Equity Hedge, Fund of Funds, Macro, Emerging Markets, and Overall hedge fund indices, Panel C of Table VI shows that the global three-factor model has smaller pricing errors than the Fama–French model and its extensions with the momentum, TERM, and DEF factors. These results are consistent with Boyson, Stahel, and Stulz (2010), Sadka (2012), and Bali, Brown, and Caglayan (2011, 2012), who find that the Fama and French U.S. stock factors do not explain the cross section of hedge fund returns very well. However, our simple value and momentum factors applied globally across asset classes do appear to capture a sizeable fraction of the returns to hedge funds.

The evidence in Table VI suggests that the global across-asset three-factor model does a good job of capturing not only the returns to value and momentum globally across asset classes, but also the returns to size and value and size and momentum in U.S. equities, as well as the cross section of hedge fund returns, providing additional testing grounds that are created from a completely different set of securities. Conversely, while local U.S. factors capture U.S. equity returns well, they do not explain a lot of value and momentum returns globally or across asset classes, nor do they capture the returns to various hedge fund strategies well. While our three-factor global model performs better in explaining all of these different test assets, the GRS test still rejects our model in all cases, suggesting that more work needs to be done to fully describe the cross section of returns.

V. Robustness and Implementation

Finally, we examine the robustness of our findings to implementation issues. A reader convinced of the efficacy of value and momentum strategies, particularly in combination, may be concerned with real world implementation issues. Though well beyond the scope of this paper, in this section we briefly discuss some practical concerns, including implementation costs and portfolio construction, as well as opportunities to improve upon our admittedly but intentionally simple approach.

A. Transaction Costs

Like most academic studies, we focus on gross returns, which are most suitable to illuminating the relation between risk and returns. However, gross returns overstate the profits earned by pursuing the strategies we examine in practice. A few papers try to examine the transaction costs and capacity of these strategies, especially momentum, perhaps due to its higher turnover. For example, Korajczyk and Sadka (2004) and Lesmond, Schill, and Zhou (2003) argue that the real world returns and capacity of equity momentum strategies are considerably lower than the theoretical results would imply. Their conclusions are based on aggregate trade data and theoretical models of transactions costs. Using live trading data, Frazzini, Israel, and Moskowitz (2012) challenge these results and show that the real world trading costs of value, momentum, and a combination of the two in equities are orders of magnitude lower for a large institution than those implied by the calibrated models of Korajczyk and Sadka (2004) and Lesmond, Schill, and Zhou (2003). As a result, Frazzini, Israel, and Moskowitz (2012) conclude that these strategies can be scaled considerably and still generate strong net returns. In addition, we focus on an extremely large and liquid set of equities in each market (approximately the largest 17% of firms), where trading costs, price impact, and capacity constraints are minimized.

Studies on trading costs also focus exclusively on individual stocks, but half of the markets that we examine are implemented with futures contracts, which typically have much lower trading costs than stocks. Hence, although our equity strategies outperform our nonequity strategies in gross returns, net of trading cost returns are likely to be much closer.

Furthermore, Garleanu and Pedersen (2012) model how portfolios can be optimally rebalanced to mitigate transaction costs and demonstrate how this improves the net performance of commodity momentum strategies, for example. In a similar spirit, Frazzini, Israel, and Moskowitz (2012) demonstrate how equity portfolios can benefit from several practical steps taken to reduce transactions costs that, while having a cost in terms of gross returns (from style drift), can improve net returns. For instance, the strategies we study here are all naively rebalanced exactly monthly no matter what the expected gain per amount traded. Varying the rebalance frequency, optimizing the portfolios for expected trading costs, and extending or occasionally contracting the trade horizon can all improve the basic implementation of these strategies.

B. Shorting

Our paper is, of course, as much about shorting assets as it is about going long. While going long versus short is symmetric for futures, shorting involves special costs in stock markets. If our results are completely dependent on shorting and if shorting is too costly or not implementable, this would certainly raise questions about the real world efficacy of these strategies. However, Israel and Moskowitz (2012) provide evidence that the return contributions of both value and momentum strategies across the same asset classes we study here are roughly equal from the long and short sides of the portfolio and that long-only portfolios of value and momentum still produce abnormal returns. Thus, these strategies are still effective even if shorting is restricted. In addition, Frazzini, Israel, and Moskowitz (2012) provide some evidence that the trading costs of shorting stocks are not materially different from the costs of buying or selling stocks, and that real-world shorting costs for a large institutional investor are not prohibitive to running sizeable funds in these strategies.

C. Portfolio Formation

In this paper we intentionally keep everything as simple as possible, both for clarity and as a precaution against the pernicious effects of data mining. In fact, one of the paper's objectives is to provide a robust out-of-sample test of ideas that have been largely tested in individual, particularly U.S., stocks and extend them to other asset classes. However, when faced with real world implementation, there are many choices to consider. For example, we look at two simple portfolio implementations in the paper: top 1/3 minus bottom 1/3, and a linear weighting scheme based on ranking securities. These are far from the only possibilities, and the choice of weighting scheme can impact not only gross returns, but also transactions costs. While we do not claim that either of these choices is optimal in either a gross or net return sense, we also explore more extreme sorts of securities into deciles and find that doing so does not materially affect the results. In the Internet Appendix we replicate our main results for individual equity markets in the United States, the United Kingdom, Europe, and Japan for decile portfolios and find very similar results. In the Internet Appendix we also plot the pricing errors of our three-factor model for these 80 decile portfolios of value and momentum in each of the four equity markets (the United States, the United Kingdom, Europe, and Japan). As the accompanying figure shows and the asset pricing statistics verify, our three-factor model does a good job of capturing these more extreme portfolio returns, too.

We also value weight stocks within our portfolios and equal weight the securities in other asset classes. However, other weighting schemes yield similar results and, because we focus on the largest, most liquid securities, trading costs are unlikely to be affected much by such changes. Hence, our main findings are robust to a variety of perturbations and portfolio formations.

D. Volatility Scaling

When we aggregate our strategies across asset classes, we ensure that the different asset classes are scaled to have similar volatility. To do so, we scale each asset class by the inverse of its realized volatility over the full sample.

However, since the full sample is not known in advance, a real world portfolio would need to scale by a measure of volatility that is estimated ex ante. For robustness, in the Internet Appendix we report results for all of our value and momentum strategies scaled to the same ex ante volatility of 2% per annum using a rolling 3-year estimate of each portfolio's volatility from daily returns. The results are reported together with the original unadjusted returns. The Sharpe ratios and correlations of the strategies are very similar and yield identical conclusions.

E. Dollar Neutral vs. Beta Neutral

As is standard in academic studies, our strategies are constructed to be \$1 long and \$1 short, but they need not have a zero market beta exposure (at the local or global level). However, real world portfolios can, and often do, attempt to create long-short portfolios that are ex ante beta neutral (in addition to, or instead of, being dollar neutral). We find that our inferences based on the strategies' alpha from factor regressions are not affected by market hedging.

F. Value and Momentum Measures

We use one measure for value and one for momentum for all eight markets we study. We choose the most studied or simplest measure in each case and attempt to maintain uniformity across asset classes to minimize the potential for data mining. In real world implementations, data mining worries may be weighed against the potential improvements from having multiple (and perhaps better) measures of value and momentum, if for no other reason than to diversify away measurement error or noise across variables. Israel and Moskowitz (2012) show, for instance, how other measures of value and momentum can improve the stability of returns to these styles in equities. Most practical implementations use a variety of measures for a given style. In fact, we set out to examine value and momentum in eight different markets and asset classes using a single uniform measure for each. Although we find positive returns to value and momentum in each asset class, these returns are not always significant. In particular, our weakest results using the current measures of value and momentum pertain to bonds, which do not produce statistically significant premia. However, as shown in Table I, Panel C, the returns can be vastly improved using other measures of value and momentum, and taking a composite average index of measures for value and momentum produces even more stable and reliable results. Hence, our use of simple, uniform value and momentum measures may understate the true returns to these strategies.

The literature on realistic implementation of these strategies is still young, and the list of choices to make when moving from an academic study like ours to implementing these strategies in practice is long. But current evidence, research, and practical experience point to the effects we study being highly applicable to real world portfolios. Consistent with this conjecture, as shown in Table VI, our simple value and momentum global factors capture a sizeable fraction of the returns to hedge fund indices, which suggests that hedge funds are engaged in similar or highly correlated strategies globally.

G. Evolution over Time

As the hedge fund industry has grown and more capital has been devoted to these strategies, it is interesting to consider what effect, if any, such activity has on the efficacy of value and momentum strategies. While a complete analysis of this question is beyond the scope of this paper, we offer a couple of results perhaps worthy of future investigation.

Table VII reports the Sharpe ratios and correlations among the value and momentum strategies over the first and second halves of the sample period—1972 to 1991 and 1992 to 2011. As the first row of Table VII, Panel A shows, the Sharpe ratios to both value and momentum have declined slightly over time. In addition, their correlations across markets have increased over time—the average correlation among value strategies has risen from 0.31 to 0.71 and among momentum strategies has risen from 0.46 to 0.77. However, the correlation between value and momentum has declined from –0.44 to –0.63, and, as a result, the Sharpe ratio of the combination of value and momentum has not changed much over time, since the increased correlation across markets is being offset by the more negative correlation between value and momentum. These results may be consistent with increased participation of arbitrageurs driving up correlations among value and momentum strategies globally.

The next row of Table VII, Panel A repeats the same analysis, splitting the sample prior to and after August 1998, which is roughly when the funding crisis peaked following the collapse of Long Term Capital Management (LTCM). The correlation among value strategies is much higher after August 1998 (0.16 pre-1998 vs. 0.64 post-1998), and the correlation among momentum strategies is also higher after 1998 (0.43 vs. 0.71). The next three rows of Table VII, Panel A report the same statistics for periods of worsening and improving funding liquidity, defined as negative and positive funding liquidity shocks, and are split separately into pre- and post-1998. Consistent with our previous regression results in Table IV, value strategies do worse when liquidity improves and momentum strategies do worse when liquidity declines, but these patterns appear only after 1998. Prior to the financial crisis of 1998, funding liquidity shocks seem to have little impact on value or momentum strategies. After 1998, however, value generates a Sharpe ratio of 0.85 during periods of worsening liquidity, but only 0.28 when liquidity improves. Conversely, momentum produces a Sharpe ratio of 0.19 when liquidity worsens, but a Sharpe ratio of 0.99 when liquidity improves. The 50/50 value/momentum combination is immune to liquidity risk, even after 1998.

Panel B of Table VII examines more formally how value and momentum correlations change over time and with liquidity shocks by running time-series regressions in which the dependent variable is the cross product of monthly returns on the various strategies to proxy for time-varying correlations. We estimate the time t correlation among value strategies globally, $\rho(Val,Val)_t$, as

Table VII

Dynamics of Value and Momentum Returns

Panel A reports Sharpe ratios and correlations among the value, momentum, and 50/50 value/momentum combination strategies across different economic environments. The first three columns report the Sharpe ratios of the all-asset-class value, momentum, and 50/50 combination strategies and the last three columns report the average correlations among value strategies globally; among momentum strategies globally, and among 50/50 value/momentum combinations globally. These statistics are reported for the two halves of the sample period, prior to and after August 1998 for the top and bottom half of observations based on our global index of liquidity shocks from Table III ("improving" and "worsening" liquidity, respectively), and the same split of improving versus worsening liquidity pre- and post-August 1998. Panel B reports time-series regressions of conditional correlations among value strategies globally; among momentum strategies globally; and between value and momentum strategies globally on a time trend, a global recession indicator (as defined in Table III), global liquidity shocks (as defined in Table III), a post-August 1998 dummy, and an interaction between the post-August 1998 dummy and liquidity shocks. The conditional correlations used as the dependent variables are estimated as the average pairwise correlations among the strategies each month using the cross product of monthly returns to each strategy as described in Section V.G.

Panel A: Dynamics of Sharpe Ratios and Correlations

	Sharpe Ratios			Correlations		
	Value	Momentum	50/50 Combination	$\rho(Val, Val)$	$\rho(Mom, Mom)$	$\rho(Val, Mom)$
1st half—1972 to 1991	0.78	0.90	1.40	0.31	0.46	−0.44
2nd half—1992 to 2010	0.68	0.71	1.43	0.71	0.77	−0.63
Pre-08/1998	0.68	1.02	1.49	0.16	0.43	−0.51
Post-08/1998	0.75	0.72	1.39	0.64	0.71	−0.55
Worsening liquidity	0.95	0.57	1.36	0.54	0.72	−0.53
Improving liquidity	0.59	0.87	1.45	0.77	0.79	−0.56
Worsening liquidity (pre-1998)	1.10	1.00	1.76	0.40	0.59	−0.30
Improving liquidity (pre-1998)	1.09	1.27	2.04	0.36	0.49	−0.29
Worsening liquidity (post-1998)	0.85	0.19	0.88	0.65	0.81	−0.71
Improving liquidity (post-1998)	0.28	0.77	1.07	0.87	0.87	−0.65

Panel B: Dynamics of Value and Momentum Correlations

Dependent variable	$\rho(Val, Val)_t$	$\rho(Mom, Mom)_t$	$\rho(Val, Mom)_t$	$\rho(Val, Val)_t$	$\rho(Mom, Mom)_t$	$\rho(Val, Mom)_t$
Time trend	0.0067	0.0181	−0.0320	−0.0011	0.0045	−0.0197
	(2.21)	(3.26)	(−4.22)	(0.20)	(0.52)	(−1.37)
Recession	0.0828	0.0971	0.0195	0.0823	0.0938	0.0206
	(1.88)	(2.31)	(0.31)	(2.05)	(2.30)	(0.34)
Liquidity shocks	0.0131	0.0519	−0.0303	0.0458	−0.0048	−0.0717
	(0.98)	(2.58)	(−1.62)	(1.80)	(−0.11)	(−1.64)
Post-08/1998				0.1212	0.2136	−0.1928
				(1.70)	(1.82)	(−0.99)
Liquidity shocks × post-08/1998				−0.0379	0.0929	0.0161
				(−1.20)	(2.11)	(0.34)

the average across asset-classes at time t of $r_{i,t}^{Val} \times r_{k,t}^{Val}$, where $r_{i,t}^{Val}$ is the return to the value strategy in market or asset class i at time t. We define $\rho(Mom, Mom)_t$, and $\rho(Val, Mom)_t$ similarly. The time series of these correlations is regressed on a linear time trend, a global recession indicator, and the time series of liquidity shocks. The first three columns of Table VII, Panel B show that the average correlation among value and momentum strategies across markets and asset classes has been significantly increasing over time and the correlation between value and momentum is significantly more negative over time. Recessions increase the correlation among both value and momentum strategies globally, controlling for the time trend. Liquidity shocks also appear to significantly increase correlations among momentum strategies, controlling for the time trend and recessions. However, the last three columns repeat the regressions adding a post-1998 dummy variable and an interaction between the post-1998 dummy and liquidity shocks. Rather than a time trend, the post-1998 dummy seems to be driving any correlation changes, and the impact of liquidity shocks on correlations also appears to be exclusively a post-1998 phenomenon. These results are consistent with an increase in the importance of liquidity risk on the efficacy of these strategies following the events of August 1998 that appear to be more important than any time trend on the increasing popularity of value and momentum strategies among leveraged arbitrageurs.[20] Hence, funding liquidity risk and limits to arbitrage activity may be a progressively more crucial feature of these strategies and future work may consider these issues in understanding the returns to value and momentum.

VI. Conclusion

We provide comprehensive evidence on the return premia to value and momentum strategies globally across asset classes, and uncover strong common factor structure among their returns. The strong correlation structure among value and momentum strategies across such diverse asset classes is difficult to reconcile under existing behavioral theories, while the high return premium and Sharpe ratio of a global across-asset-class diversified value and momentum portfolio presents an even more daunting hurdle for rational risk-based models to accommodate than the more traditional approach of considering value or momentum separately in a single asset market. Although both behavioral and rational theories for value and momentum focus predominantly on equities, the existence of correlated value and momentum effects in other asset classes—with their different investors, institutional structures, and information environments—argues for a more general framework.

We further find that exposure to funding liquidity risk provides a partial explanation for this correlation structure, especially following the funding crisis of 1998, but leaves much to be explained. While the relation to funding liquidity

[20] Israel and Moskowitz (2012) examine the relation between size, value, and momentum profitability and aggregate trading costs and institutional investment over time. They find little evidence that the returns to these strategies vary with either of these variables.

risk could imply that limited arbitrage activity may contribute to the prevalence and dynamics of these phenomena, we leave the ubiquitous evidence on the efficacy of value and momentum across the diverse asset classes we study, its strong correlation structure, and intriguing dynamics related to funding risk as a challenge for future theory and empirical work to address.

Finally, we provide a simple global three-factor model that describes a new set of 48 global across-asset-class test assets, the Fama–French portfolios, and a variety of hedge fund indices. In further investigating the underlying economic sources driving value and momentum returns, we hope this simple three-factor framework can be useful for future research that is becoming increasingly concerned with pricing global assets across markets.

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