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Deep Value

Cliff Asness, John Liew,
Lasse Heje Pedersen, and Ashwin Thapar

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Cliff Asness, John Liew, Lasse Heje Pedersen, and Ashwin Thapar

Cliff Asness
is a managing and founding principal at AQR Capital Management in Greenwich, CT.
cliff.asness@aqr.com

John Liew
is a founding principal at AQR Capital Management in Greenwich, CT.
john.liew@aqr.com

Lasse Heje Pedersen
is a principal at AQR Capital Management in Greenwich, CT, and a professor at Copenhagen Business School in Copenhagen, Denmark.
lasse.pedersen@aqr.com

Ashwin Thapar
is a principal at AQR Capital Management in Greenwich, CT.
ashwin.thapar@aqr.com

KEY FINDINGS

- The evolution of asset returns and fundamentals around *deep value episodes*—defined as periods with an especially wide valuation spread between cheap and expensive securities—offers a new window to understand markets and differentiate competing theories of the value premium.
- Deep value episodes have historically been characterized by poor past performance of value investing and high future returns to value investing.
- During these episodes, value stocks experience worsening earnings fundamentals, negative sentiment in news stories, selling pressure, and higher limits to arbitrage; nevertheless, sophisticated arbitrageurs pursue these opportunities.

ABSTRACT

The authors define *deep value* as episodes in which the valuation spread between cheap and expensive securities is especially wide relative to its history. Examining global individual equities, equity index futures, currencies, and global bonds, the authors find that deep value is (1) highly compensated; (2) related to worsening fundamentals; (3) associated with higher risk but not fully explained by known risk factors; and (4) characterized by selling pressure related to overextrapolation of past returns and, although arbitrageurs take the other side, they face elevated trading costs and risk. These findings support a theory of return extrapolation driving the value risk premium over other behavioral and rational explanations.

TOPICS

*Global markets, portfolio construction, risk management, quantitative methods**

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Why are certain securities cheaper than others, and why is the price gap sometimes especially large? We seek to shed new light on these questions by studying *deep value* episodes in which valuation differences of cheap securities relative to expensive ones are unusually large relative to history. We construct a novel dataset with over 3,000 such deep value episodes across multiple geographies and asset classes using almost a century of data. Using these data, we find that deep value episodes are associated with particularly high future returns to buying cheap securities and selling expensive ones. We show that during these episodes, deep value securities have deteriorating fundamentals,[1] so their abnormal cheapness

[1] Note that in what follows when we refer to *deep value* we are referring to the difference between cheap and expensive portfolios (during a deep value episode). For example, if we say deep value securities have deteriorating fundamentals, we mean that the fundamentals of the cheap portfolio are deteriorating relative to those of the expensive portfolio. Note that the deteriorating fundamentals to

is, at least partly, justified. However, the high return of deep value is not explained by known risk factors, so something more must drive the low pricing of these deep value securities. Our evidence suggests that on average the prices of deep value securities fall more than their fundamentals would suggest, as some investors create selling pressure related to negative sentiment and overextrapolation of past returns. Furthermore, we find evidence that although arbitrageurs take the other side, buying deep value, their ability to do so is limited by high trading costs and risk.

To understand our findings, consider a simple framework based on Gordon's growth model that relates stock i's dividend yield D/P_i to its expected return $E(r^i)$ and its growth rate g^i:

$$D/P_i = E(r^i) - g^i \tag{1}$$

We see that a stock's relative cheapness (high D/P_i) must be due to either higher expected returns or lower expected growth.

We first examine the link between valuation and expected returns, which can be done using static or dynamic empirical tests. The static test amounts to considering the average returns of the value strategy (i.e., buying cheap stocks with high D/P_i while shorting expensive ones), whereas the dynamic test amounts to determining whether the returns to the value strategy during deep value episodes, when the valuation spread between cheap and expensive is particularly large, are greater than average. We reconfirm the findings in the literature that the returns to the static value strategy are positive on average and greater when value spreads are wide.[2] Although we add little to the existing literature on the static value premium, we vastly extend the evidence on the latter, dynamic effect. Given the lack of extreme events in a single time series, we increase statistical power using a novel approach that separately evaluates deep value events within subsets of each universe (e.g., deep value within US auto stocks and Japanese industrial stocks) and then pools these events across subsets, regions, and asset classes. Using this approach, we show broad evidence of deep value outperforming standard value across multiple asset classes, geographies, and time periods. We also show that our approach can be used in an implementable deep value trading strategy that generates significant alpha over other known factors, including standard value and momentum.

Having confirmed the existence of both the static value and dynamic deep value premiums, we next take a closer look at market behavior during these deep value episodes. We use that evidence to try to distinguish between competing theories of the value effect. In particular, we seek to differentiate between theories of the value premium being driven by (1) rational compensation for risk, (2) noise in prices, or (3) behavioral biases and limited arbitrage.[3]

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deep value securities could be coming from the fact that the expensive portfolio (which we are short) has appreciating fundamentals.

[2] Value strategies have been found to deliver positive returns in almost all global asset classes in which they have been examined (Asness, Moskowitz, and Pedersen 2013), including US equities (Stattman 1980; Rosenberg, Reid, and Lanstein 1985; Fama and French 1992; Lakonishok, Shleifer, and Vishny 1994), global equities (Fama and French 1998; Liew and Vassalou 2000), country equity indexes (Asness, Liew, and Stevens 1997), and other global asset classes such as currencies (Asness, Moskowitz, and Pedersen 2013). Value spreads have been found to predict value returns (Asness et al. 2000; Cohen, Polk, and Vuolteenaho 2003).

[3] Black (1986) stated that "noise is contrasted with information" and can arise, for instance, from demand pressure unrelated to information about fundamentals. Rational theories include the standard capital asset pricing model (CAPM), which cannot explain the value effect (Fama and French 1992); the conditional CAPM performs better (Gomes, Kogan, and Zhang 2003) but has been rejected by Lewellen and Nagel (2006). Daniel, Hirshleifer, and Subrahmanyam (1998) proposed a behavioral model of overreaction to fundamentals; Barberis, Shleifer, and Vishny (1998) modeled investors who underreact

Our second finding is that fluctuations in valuations are linked to fluctuations in economic fundamentals, captured by g^i in the simple model presented earlier. We find that forecasted and realized earnings of cheap stocks are generally lower than those of expensive stocks, and this relation is particularly pronounced during deep value episodes.[4] This clear link between valuation and fundamentals—in addition to the fact that deep value episodes tend to be correlated across asset classes, clustering at certain times—allows us to reject theory (2) that the value premium is driven by random noise in prices, which would have indicated no relationship between valuations and fundamentals.

To evaluate the alternative rational and behavioral theories, our third set of tests considers the risk of value strategies. In a rational model, a stock's expected return depends on its risk exposure and the risk premium, $E(r^i) = (risk^i) \times (\text{risk premium})$. Thus, a cheap stock with high expected return must be risky. Furthermore, during deep value events (when these stocks are particularly cheap and have particularly high expected returns), such stocks must have a particularly high risk. Our third empirical finding is that there is mixed evidence for greater risk of deep value strategies. Value strategies have market betas close to zero both on average and during deep value episodes, leading us to reject the idea that value returns are rational compensation for capital asset pricing model (CAPM)-based market risk in either a static or dynamic sense. We also consider a second possibility: that deep value relates to an elevated loading on a global value factor. This test (which is only possible in a dynamic context and only with many value strategies—both unique features of our setting) can uncover a potential rational explanation based on a risk factor other than equity market beta. Indeed, we do observe that the loading of individual value strategies on the global value factor, which is naturally positive on average, is elevated during a deep value episode. However, a challenge to this explanation is that, when forming our deep value trading strategy, we still see meaningful alpha to traditional value strategies. In other words, the outsized return to deep value appears to be more than just a greater loading on the value risk factor. Overall, the evidence for rational theories, based on the two risk factors we examine, is weak.

Our fourth and final strand of empirical analysis explores the hypothesis that behavioral biases among some investors cause valuation gaps that persist owing to limited arbitrage capital among rational investors. In the context of our model, this can be interpreted as the objective (e.g., unbiased) expected return $E(r^i)$ and growth g^i for value stocks differing from the expectations of behavioral investors. If behavioral investors influence the prices of value stocks, their biases mean that value stocks have higher *risk-adjusted* returns. That is, $E(r^i) > (risk^i) \times (\text{risk premium})$. Our previous three findings, using static and dynamic evidence, of strong returns to deep value that are fundamentally driven and not explained by loadings on risk factors are all consistent with this behavioral explanation. However, to test these explanations at a deeper lever, we examine direct evidence for investor behavior driving the deep value effect. To this end, we document negative sentiment[5] and investor selling pressure that may cause deep value episodes. Furthermore, we document evidence of widening limits to arbitrage that may explain the persistence of deep value. Finally, consistent with the idea that deep value is viewed as an opportunity by informed investors, we find that proxies for informed investors indeed appear to trade on deep value, in particular

to mixed fundamental news but overreact to series of good or bad news; theories of overextrapolation of past returns include those from Hong and Stein (1999), Barberis and Shleifer (2003), and Barberis et al. (2015).

[4] The static result broadens that of Fama and French (1995) and Cohen, Polk, and Vuolteenaho (2003); the dynamic result is novel to our knowledge.

[5] To capture the sentiment investors in value and growth stocks, we use news sentiment data from RavenPack.

short sellers, firms issuing and repurchasing their own shares, and participants in the market for corporate takeovers.[6] In other words, during deep value episodes, we find greater short selling of growth stocks, greater share issuance by expensive growth companies, and a greater frequency of acquisitions of value companies.

Finally, to distinguish between the different behavioral theories, we analyze what makes behavioral investors sell value stocks during deep value episodes. To capture the actions of investors in value and growth stocks, we use signed order flow data based on the Lee and Ready (1991) method, as done by Chordia, Roll, and Subrahmanyam (2002, 2005, 2008). We see that value stocks experience less buying pressure on average than do growth stocks and that this discrepancy is more pronounced during deep value episodes. In other words, investors display an aversion to value stocks that is most extreme during deep value episodes, but what drives this behavior? Two candidates proposed in the literature (see references in footnote 2) are overreaction to trends in fundamentals and overextrapolation of past returns. Preceding deep value episodes, value stocks tend to have both poor fundamentals and negative returns, so we need to dig deeper to distinguish these theories. In a multivariate regression designed to distinguish these effects, we find that investors' buying and selling pressures are driven by past returns but not by fundamentals. In other words, investors over-extrapolate returns and when controlling for this effect, investors appear to underreact to fundamentals.[7] Interestingly, the negative relative order flow for value stocks persists for up to a year following deep value events. Said differently, although it is perhaps unsurprising that investors run away while stocks are cheapening, it is interesting that they continue to do so even after prices start to recover.

In summary, we find that deep value episodes occur when a history of low returns leads to dismal investor sentiment and selling pressure of value stocks (relative to growth stocks), coupled with limited arbitrage for the informed investors taking the other side. Deep value episodes are correlated across asset classes, clustering in time, and out-of-sample returns are abnormal even when controlling for traditional factors such as standard value and momentum.

THEORY

To understand the motivation for considering value spreads and deep value opportunities, we consider a simple unified framework that illustrates the predictions of all the competing theories. For any security *i* at time *t*, we denote its price by P_t^i and its relevant scaling variable by B_t^i. For instance, a natural scaling variable B_t^i for stocks and stock indexes is the book value (or dividends, cash flows, or other proxies for the fundamental value), for currencies it is the exchange rate consistent with purchasing power parity, and for bonds it is the present value based on inflation. For simplicity, we refer to B_t^i as the *book value* in all cases.

We are interested in each security's valuation ratio, that is, the book-to-price ratio denoted by $V_t^i = \frac{B_t^i}{P_t^i}$. Securities with high book-to-price (B/P) are cheap value securities, whereas those with lower B/P are expensive growth securities. We construct a value strategy by going long a portfolio *H* of value securities with high valuation ratios while shorting a portfolio *L* of growth securities with low values. In other words, the

[6] See also Dong, Hirshleifer, Richardson, and Teoh (2006), Edmans, Goldstein, and Jiang (2012), and Hong, Wang, and Yu (2008).

[7] In a similar spirit, the well-known post-earnings announcement drift (Ball and Brown 1968) is consistent with underreaction to fundamentals on average, and so is the high return to quality stocks (see Asness, Frazzini, and Pedersen 2019). Indeed, quality stocks have good fundamentals; if investors underreacted to such fundamentals on average, then this underreaction could help explain the positive risk-adjusted returns of quality stocks.

high-minus-low value strategy is characterized by going long assets that are cheaper than those shorted, $V_t^H > V_t^L$. We define the value spread as the difference in valuation ratios for the H versus L portfolios:

$$Value\ spread_t := \log(V_t^H) - \log(V_t^L) \tag{2}$$

Clearly, the value spread is positive by definition for the value portfolio. Empirically, we first compute the aggregate valuation ratio for the long and short portfolios for each of our strategies and then compute the value spread as the difference in the logarithm of these valuation ratios. We use the logarithm because this corresponds to a percentage difference in valuation ratios.

We develop the theory in detail in the online Appendix, and here we summarize the main predictions as illustrated in Exhibit 1. As seen in the exhibit, we analyze four leading theories of value (listed in the top row), and we provide a unified theoretical framework for all these competing theories. Empirically, we document four key stylized facts about value (seen in the first column), which serve as tests of the competing theories, where "x" means rejection of the theory and a check mark indicates consistency with the theory. To understand the rational asset pricing theory in the first column, note that the rational theory says that we can write the value spread in terms of the risk premium (λ_t), the risk exposures (or betas, β_t^H, β_t^L) of the H and L portfolios, and the growth rates of these portfolios (g_t^H, g_t^L):

$$Value\ spread_t \cong \lambda_t(\beta_t^H - \beta_t^L) - (g_t^H - g_t^L) \tag{3}$$

We see that, according to the rational theory of asset pricing, the value spread should be higher if the value portfolio has a particularly high-risk exposure relative to the growth portfolio (high $\beta_t^H - \beta_t^L$) or if value stocks have lower growth rates than growth stocks (low $g_t^H - g_t^L$), or some combination. In contrast, theories of pure noise in prices predict that the value spread is unrelated to fundamentals.

$$Value\ spread_t \cong Noise \tag{4}$$

EXHIBIT 1

Summary of Findings and Relation to Competing Theories

Our Findings	Rational Theories	Noise in Prices	Behavioral Overreaction to Fundamentals	Behavioral Over-Extrapolation of Returns
1. Deep value has greater returns than does shallow value	✓	✓	✓	✓
2. Deep value has fundamental drivers				
– Fundamentals worsen before deep value episodes	✓	×	✓	✓
– Deep value episodes cluster	✓	×	✓	✓
3. Deep value is not explained by known risk factors				
– No market beta	×	✓	✓	✓
– Has high value beta, but	✓	✓	✓	✓
– Has alpha over known risk factors	×	✓	✓	✓
4. Deep value is linked to the behaviors of investors and arbitrageurs				
– Negative news sentiment			✓	✓
– Selling pressure			✓	✓
– Selling driven by past returns, not past fundamentals			×	✓
– Limited arbitrage			✓	✓
– But informed investors capitalize			✓	✓

As seen in Exhibit 1, our evidence is not consistent with such pure noise because deep value episodes are linked to movements in fundamentals.

Thus, this evidence favors the rational theory, but an additional prediction of the rational theory is that the value spread should only predict the return of the value portfolio to the extent that the spread arises from risk differences:

$$E_t(r_{t+1}^{value}) = \lambda_t(\beta_t^H - \beta_t^L) = \lambda_t \beta_t^{value} \tag{5}$$

As seen in Exhibit 1, the evidence does not support this prediction, at least when we look at standard risk factors.

Lastly, we consider behavioral models in which security returns are not mainly driven by differences in risk but, instead, by behavioral biases. We consider two such behavioral models, one driven by overreaction to fundamentals and another by overextrapolation of past returns. In the former

$$\textit{Value spread}_t \cong -(1+z_t)(g_t^H - g_t^L) \tag{6}$$

where $z_t \geq 0$ is the degree of overreaction in this asset class at time t. Therefore, this theory also links the value spread to fundamentals; furthermore, the value spread is linked to expected return, in which the expectation is taken from the perspective of the empirical researcher (i.e., the objective expectation):

$$E_t(r_{t+1}^{value}) \cong \textit{Value spread}_t - (g_t^H - g_t^L) \cong z_t(g_t^L - g_t^H) \tag{7}$$

We see that under this behavioral theory, the value portfolio has a positive expected return to the extent that investors overreact, $z_t > 0$. Furthermore, the expected return is increasing by the degree of overreaction, z_t, multiplied by the spread in growth rates (as seen from the last expression) or, equivalently, in the valuation spread adjusted for the growth-rate spread (the second-to-last expression).

A related, but slightly different, behavioral view is that people over-extrapolate past returns, behaving as if the growth rate is $g_t^i + z_t r_{t-k,t}^i$ (rather than its true value g_t^i), where $r_{t-k,t}^i$ is the past return and $z_t \geq 0$ is the degree of overreaction in this asset class at time t.[8] In this case, the value spread is driven by growth rates and past returns:

$$\textit{Value spread}_t \cong -(g_t^H - g_t^L) + z_t(r_{t-k,t}^L - r_{t-k,t}^H) \tag{8}$$

and the objective expected return of the value portfolio is driven by the degree of over-extrapolation and the difference in past returns:

$$E_t(r_{t+1}^{value}) \cong z_t(r_{t-k,t}^L - r_{t-k,t}^H) \tag{9}$$

As seen from Exhibit 1, the two behavioral theories have several other common predictions: They predict that behavioral investors have negative sentiment about value stocks, especially around deep value events. This negative sentiment leads to selling pressure from these investors—in one case driven by overreaction and in the other case driven by over-extrapolation—and this selling pressure depresses prices. In addition, both theories predict that arbitrageurs will step in to profit from taking the other side but will be limited in their ability to do so by costs and risks.

[8] Here we make the simple assumption that past returns affect investors' expectations about future fundamental growth rates, whereas Barberis et al. (2015) considered investors who forecast future returns by extrapolating past returns.

DATA AND METHODOLOGY

For brevity, we provide a high-level overview of our approach and save a detailed one for our online Appendix. We study value across seven major markets, including four stock selection (SS) strategies in the United States (US), the United Kingdom (UK), Continental Europe (EU), and Japan (JP) and three asset allocation (AA) strategies in global developed equity index futures (EQ), government bond futures (FI), and currency forwards (FX). In each market, we consider two types of value strategies. First, a standard approach that builds long–short value portfolios over the full available region (e.g., all liquid US stocks or G10 FX forwards, denoted *standard*). Second, we take a novel, more granular, approach denoted *intra*. Intra strategies sort assets within subsets of each region—specifically, within industries in each SS region and pairs of each macro asset. For example, we consider a value strategy within US autos and similarly within each industry in each region. In AA, we consider, for example, a value strategy for the fixed-income pair of Bunds versus Gilts and so on. This intra approach provides many more observations of deep value opportunities.

In each asset class, we consider a standard value metric: B/P for individual stocks and equity indexes, purchasing power parity for FX, and real bond yields for fixed income. In all asset classes, we build long-only quintile-sorted portfolios as well as long–short value strategies. The long–short value strategies are formed by ranking all assets (both in the full universe and the subsets as described earlier), going long the top third and short the bottom third. For AA pairs, we always go long the cheaper asset and short the more expensive asset. For our value portfolios, we compute value spreads as described in the theory section and define deep value episodes in each strategy as periods when the value spreads exceed their 80th percentile historically.

THE RETURNS OF DEEP VALUE

In this section, we consider whether value strategies have higher future returns on average when cheap stocks are especially cheap relative to expensive ones. In other words, we examine whether time variation in value returns can be predicted by value spreads. As we will see, we find strong evidence of such variation across our global asset classes, which sets the stage for our examination of a deep value trading strategy.

In-Sample Regression Analysis

We regress the long–short value strategy return VAL_{t+1}^{i} in asset class i on the corresponding ex ante value spread, based on the insights from the theory section:

$$VAL_{t+1}^{i} = \alpha + \beta \; VALUE \; SPREAD_{t}^{i} + \varepsilon_{t+1}^{i} \tag{10}$$

We run the regression on a monthly basis, using as the dependent variable the next 12-month return to the corresponding value strategy. Our *t*-statistics account for overlapping data by clustering standard errors for correlation in both the time series and cross section, according to the method of Hansen and Hodrick (1980). Using 12-month future returns is helpful because it is a simple way to partially mitigate the countervailing momentum effect; indeed, we get similar regression results using one-month return controlling for momentum as a right-hand side variable. Furthermore, using 12-month returns may better resemble the experience of actual value investors.

EXHIBIT 2

Larger Value Spreads (Deep Value) Predicts Higher Value Returns

		Standard		Intra	
		Beta	R^2	Beta	R^2
Panel A: All Asset Portfolios					
All Assets	Estimate	0.2	15.5%	0.1	6.1%
	(*t*-statistic)	(4.0)		(10.7)	
Stock Selection (SS)	Estimate	0.3	15.9%	0.1	5.8%
	(*t*-statistic)	(3.6)		(8.5)	
Asset Allocation (AA)	Estimate	0.2	9.6%	0.1	4.0%
	(*t*-statistic)	(2.9)		(7.5)	
Panel B: Stock Selection Portfolios					
United States (US)	Estimate	0.3	15.6%	0.1	5.4%
	(*t*-statistic)	(2.7)		(7.2)	
Japan (JP)	Estimate	0.4	12.8%	0.1	6.0%
	(*t*-statistic)	(2.6)		(2.9)	
Continental Europe (EU)	Estimate	0.4	16.5%	0.1	6.3%
	(*t*-statistic)	(2.7)		(3.4)	
United Kingdom (UK)	Estimate	0.14	5.6%	0.05	5.6%
	(*t*-statistic)	(1.3)		(3.3)	
Panel C: Asset Allocation Portfolios					
Equity Indexes (EQ)	Estimate	0.3	11.5%	0.1	3.8%
	(*t*-statistic)	(2.1)		(6.6)	
Fixed Income (FI)	Estimate	0.1	12.1%	0.1	5.1%
	(*t*-statistic)	(2.6)		(6.0)	
Currencies (FX)	Estimate	0.4	14.7%	0.2	6.3%
	(*t*-statistic)	(2.9)		(8.5)	

NOTES: This exhibit shows the results of regressing 12-month-ahead value returns on value spreads at the start of each period. Standard regressions are individual time-series regressions run within each SS region or asset class. Intra regressions are pooled regressions, pooling across all industries within a region (SS) or all pairs within an asset class (AA). We also report pooled regression results at the overall stock selection, overall asset allocation, and all asset level. We report *t*-statistics in parenthesis, and note that all pooled regressions are run with entity fixed effects, and standard errors are corrected for correlation in the time series and cross section using the method of Hansen and Hodrick (1980).

Exhibit 2 reports the results. Focusing first on the results for SS, we see that the slope coefficient β is positive for both standard and intra portfolios in each of the four regions that we study (US, Japan, Europe, and UK), and the coefficient is statistically significant in seven of the eight cases at a 1% significance level. In addition, when we pool these SS strategies as shown in Panel A, the coefficient is significantly positive.

Similarly, for each of the AA strategies (equity indexes, fixed income, currencies), the predictive regressions show a positive and significant relation between current value spreads and the next 12-month excess return to the standard and intra value strategies. When we pool all three of the asset classes together, the results remain strong. Finally, as expected, when we pool across the four stock regions and the three asset classes, we get our strongest results, which support a positive predictive relationship when using value spreads to predict value returns. In addition to the regression-based evidence of in-sample predictability, in the online Appendix we conduct quintile sorts of value returns sorted by value spreads, which indicate monotonic positive relationships.

Deep Value Returns in Event Time

Exhibit 3 presents an intuitive illustration of the returns to deep value. The dynamic return to deep value is illustrated in the right panel, whereas the left panel shows the standard static result that value stocks outperform growth stocks on average.

Focusing on the right panel of Exhibit 3, we consider the evolution of long–short value strategy returns in event time for value portfolios occurring in different value spread environments. Specifically, for each value strategy, we compute quintile break points for valuation spreads and perform event studies for each time period *t* to track the evolution of returns before and after time *t* and plot the average for each quintile portfolio. For example, the blue line, corresponding to deep value time periods, represents the average of all value strategies before and after time periods when their valuation spreads were in their top quintile. We freeze the portfolio as of time *t* and track characteristics 24 months before and after time *t*. In this way, we can see how portfolio characteristics evolved to result in deep value and how they evolved afterwards. For flowlike variables (including returns), we cumulate results and normalize such that the cumulative is zero at event time zero. We do the same for each of the other value spread quintiles to produce the remaining four lines on the event study. This structure will be repeated in future figures and analyzed in the next two sections, in which we will depict the evolution of fundamentals, risk, and behavioral characteristics, rather than return.

The top part right part of Exhibit 3 shows results for SS portfolios, in which we averaged data across sorts conducted within each industry (intra) and the overall universe (standard). The fact that the cumulative returns are falling before event time 0, for all lines, simply means that value portfolios tend to go long securities that have performed worse than those that it tends to go short. In other words, stocks become cheap by falling in price, on average (see DeBondt and Thaler 1985). Not surprisingly, this fall in price is more pronounced when the value spread is wider because losses to valuation portfolios are one mechanism via which value spreads widen. The increasing cumulative returns to the right of event time zero, for all lines, reflect that value investing works on average. More importantly, the fact that the slope is steeper for the deep value portfolios than for the other value spread portfolios means that value investing works better when the value spread is wide, consistent with the predictive regression. In addition, the event study demonstrates that the difference persists over several years, on average (and no sign that the effect ends at 24 months).

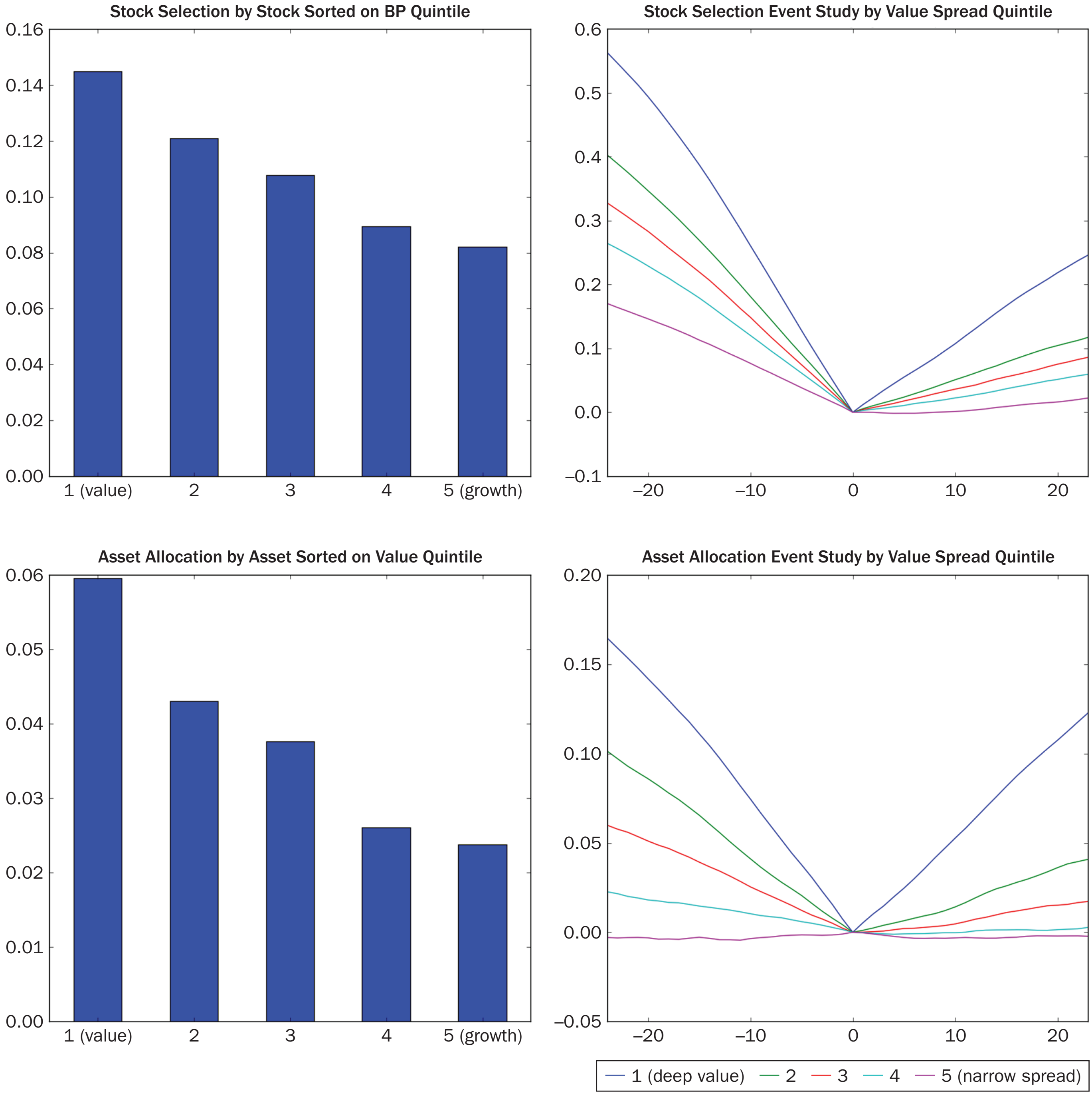
The bottom right plot of Exhibit 3 shows that similar conclusions hold up when looking at AA. The event-study plot shows, again, that value portfolios go long assets that have underperformed the short over the past two years, on average, and that these portfolios profit over the following two years, especially the deep value portfolio.

Importantly, we see both for stocks and especially for other assets that the return after portfolio formation is less positive than the cumulative loss of these assets before portfolio formation, reflecting that the initial decline in these assets was partly justified by deteriorating fundamentals, as we study further later. Note that, given the freezing of portfolios, this does not also imply that a dynamic value strategy would have been a net loser over this period because a dynamic value strategy may only buy after the price has declined (part of the way).

Out-of-Sample Trading Strategy

Having studied the in-sample returns of deep value, we next consider the strategy's out-of-sample performance. Because behavioral theories predict that arbitrageurs can profit from deep value investing (at least to a limited extent), these profits are only meaningful if they can be a realized out of sample. That is, it remains to be

EXHIBIT 3
The Returns to Deep and Shallow Value



NOTES: The top panels show the performance of value investing in stocks selection and the bottom panels in AA. The bar in the left panels shows a bucket sort of the level of returns for assets falling into different quintiles of valuations. The right panels show an event study tracking historical and future returns to value portfolios having different levels of valuation spreads.

seen whether one can profit from deep value when deep value events are identified without the benefit of hindsight.

To conduct a simple and realistic out-of-sample test, we start by constructing deep value trading strategies based on our previously defined standard value factors. The strategy is intended to simulate a trader opportunistically entering value trades after observing wide value spreads and exiting after observing convergence. Specifically, in each of the seven test markets, when we observe value spreads crossing the 80th percentile filter, we add that market's long–short value portfolio, as of that point in time, to the deep value portfolio.[9] After being added, these opportunistic trades remain in the deep value portfolio until valuation spreads have declined below their historical median without being rebalanced.

Exhibit 4 reports the alphas of these global deep value strategies from 1976 to present, when we have data available for both stocks and macro asset classes. For each deep value strategy, we run a regression of the excess returns on both the market, as measured by MSCI world, and untimed value and momentum factors. Here, untimed value and momentum factors refers to factors that are constructed to exactly match the investment universe and portfolio construction of those used in the deep value strategy, except that we trade all underlying value portfolios without filtering for a wide valuation spread. In other words, for the intra deep value strategies, the untimed value and momentum strategies on the right-hand side of the regression are also formed on an intra basis.

Panel A shows the deep value alphas for the seven standard value strategies, and Panel B considers the intra strategies. We report results individually for each market, combined for all SS strategies, combined across all AA strategies, and combined across all strategies (ALL). The overall SS deep value strategy is an equal risk-weighted average of the four regions, and, similarly, the overall AA deep value strategy is the risk-weighted average of the corresponding equity index, FX, and bond strategies. The ALL deep value strategy is an equal risk-weighted average of SS and AA.

We generally see the intuitive result that each deep value strategy has a significant loading on the corresponding untimed value strategy.[10] We also see that deep value has a significant negative loading on momentum, even controlling for value, indicating that the momentum of deep value assets is even more negative than that of untimed value. This is intuitive because deep value assets tend to have particularly negative past returns, as seen in Exhibit 3. Indeed, the strategy buys value portfolios after value spreads have risen (typically associated with the value portfolio losing money) and sells value portfolios when valuations spreads have fallen (typically associated with a profitable period for value). The loadings on the market are mixed but generally negative.

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[9] Each trade that is added to the portfolio is scaled to target a fixed level of annualized volatility so that trades in different asset classes have comparable risk allocations (because we later rescale at the portfolio level, the actual level of the risk target at this intermediate step is unimportant). To do this, we measure the expected volatility of each trade portfolio on an unlevered basis and then scale leverage to achieve the target volatility. In SS strategies, the measure of expected volatility is the volatility of the trailing one-year daily returns of the value strategy in the given region and asset class. Conversely, in AA strategies, in which different assets can have very different volatilities, we measure the trailing one-year daily volatility of the specific trade portfolio.

[10] Asness et al. (2017) found that using value to time nonvalue factors leads to a strategy that is correlated to value, and investors not accounting for this may end up with a (suboptimal) increase in their value exposure. Deep value is also a value-based timing strategy; however, the correlation to value that we see here is more trivially obvious because deep value is long value (when it is cheap) or has no position. It can never be short value. As before, investors should account for this correlation when allocating to deep value, as explored later in this section.

EXHIBIT 4

The Performance of Deep Value Out-of-Sample

	SS Portfolios				AA Portfolios			Aggregated Portfolios		
	US	JP	EU	UK	FX	FI	EQ	SS	AA	ALL
Panel A: Deep Value Constructed on Standard Value Strategies										
Annualized Alpha	0.5%	0.5%	0.9%	–0.5%	1.5%	1.0%	1.3%	0.7%	3.3%	3.5%
(*t*-statistic)	(0.6)	(0.5)	(0.9)	(–0.5)	(2.0)	(2.1)	(2.1)	(0.9)	(3.9)	(3.0)
Market	–0.02	–0.02	–0.03	–0.04	–0.04	0.01	–0.01	0.00	–0.05	–0.05
(*t*-statistic)	(–1.2)	(–0.8)	(–1.2)	(–1.4)	(–2.2)	(0.7)	(–0.9)	(–0.1)	(–2.4)	(–1.7)
Value	0.24	0.19	0.22	0.33	0.31	0.07	0.19	0.27	0.31	0.47
(*t*-statistic)	(11.3)	(8.5)	(8.5)	(11.7)	(17.1)	(5.0)	(10.0)	(11.2)	(13.1)	(13.8)
Momentum	–0.09	–0.05	–0.06	–0.01	–0.05	0.02	–0.02	–0.09	–0.07	–0.10
(*t*-statistic)	(–4.4)	(–1.8)	(–2.2)	(–0.5)	(–2.8)	(1.7)	(–1.3)	(–3.6)	(–2.9)	(–2.9)
R^2	37%	27%	31%	35%	41%	7%	21%	33%	30%	37%
Panel B: Deep Value Constructed on Intra Value Strategies										
Annualized Alpha	3.0%	–0.5%	4.5%	5.2%	1.9%	2.6%	2.1%	3.5%	2.5%	6.4%
(*t*-statistic)	(2.7)	(–0.4)	(3.0)	(2.9)	(1.8)	(1.8)	(1.8)	(4.2)	(3.0)	(5.1)
Market	–0.03	–0.02	0.02	–0.06	–0.04	0.02	0.03	–0.05	–0.02	–0.07
(*t*-statistic)	(–1.0)	(–0.5)	(0.5)	(–1.3)	(–1.5)	(0.5)	(1.0)	(–2.5)	(–0.9)	(–2.4)
Value	0.52	0.55	0.57	0.23	0.50	0.37	0.45	0.41	0.35	0.61
(*t*-statistic)	(19.2)	(15.7)	(15.3)	(6.8)	(21.8)	(10.3)	(15.1)	(17.7)	(14.7)	(18.2)
Momentum	–0.15	–0.11	–0.06	–0.20	–0.14	–0.14	–0.20	–0.14	–0.15	–0.27
(*t*-statistic)	(–5.4)	(–3.1)	(–1.6)	(–4.5)	(–5.5)	(–3.9)	(–6.5)	(–6.1)	(–6.5)	(–8.0)
R^2	57%	52%	54%	24%	54%	26%	43%	52%	39%	53%

NOTES: This exhibit shows the returns to our out-of-sample deep value trading strategies regressed on known factors. The deep value strategy buys value portfolios when the value spread exceeds the 80th percentile (using only known data at each time) and sells when the value spread reverts to its median level. We regress the returns to this strategy on excess returns to the market (MSCI World) and value and momentum factors that are constructed as those used in the deep value strategy but without filtering for wide valuation spreads (e.g., for the intra deep value strategy, the right-hand-side value and momentum strategies are also formed on an intra basis). We run these regressions for the standard full cross section (Panel A) and for the intra strategies (Panel B).

The alphas of the standard deep value strategies are positive in most cases but mixed in terms of magnitude and statistical significance. In SS, all the alphas are insignificant. This indicates that, although the standard deep value strategy may be profitable when it stands alone, its profitability is derived largely from its loading on a regular value strategy, with a limited benefit of using the information contained in any one value spread to time the amount of exposure. In other words, timing any one value strategy would not be meaningfully additive in the context of a portfolio with optimal allocations to untimed value and momentum, consistent with the work of Asness at al. (2017). However, when we put all seven strategies together (the column in the exhibit labeled ALL), we see a significant alpha.

The power of diversifying across many value strategies is far greater when we turn to our 515 intra value strategies within the seven test markets. Specifically, the intra strategies separately track value spreads within each industry in each stock market and each pair of assets in AA. Looking at each intra substrategy, we continue to enter a trade when the value spread is at its 80th percentile and exit at the 50th percentile.[11] In other words, in each of the seven test markets, rather than the deep value trade simply being on or off for the entire market (as in the aforementioned

[11] For practicality purposes, we cap each strategy to target at most 20 times the individual trade level risk target (if more than 20 trades exist in the portfolio, we start to proportionally reduce the risk target per trade), although this capping does not meaningfully affect results.

standard specification), the intra deep value strategy may be on for auto stocks and biotech stocks while being off for other industries. Furthermore, the intra deep value strategy granularly varies risk according to the number of deep value trades that exist, taking more risk when more sectors experience deep value events.

The performance of the intra deep value strategies is presented in Panel B of Exhibit 4. The intra deep value strategy shows significant alphas in three of the four equity markets (in which we had seen weak results for the standard deep value strategy), as well as in the diversified strategies in SS, AA, and overall. This higher alpha is particularly impressive given that, in SS, performance for the intra value strategy used as a control variable in this regression is much stronger than for the standard value strategy (used in the regression with the standard deep value strategy). The overall strategy has an alpha of over 6.4% with a *t*-statistic exceeding 5. In other words, we see that, although there is little information content in any one value spread, the aggregate information across many value spreads is significant. In the online Appendix, we additionally show that the significant alpha of deep value is robust to a variety of different specifications, including changing the thresholds for trade entry and exit or eliminating thresholds altogether and simply scaling portfolio exposures based on the value spreads in a linear fashion.

Deep Value Returns and the Number of Simultaneous Deep Value Events

Finally, we look at how the total number of deep value opportunities varies over time. Exhibit 5 shows the number of intra deep value trades that are triggered at each time point. We see that the number of deep value events tends to cluster, with the largest peak around the Internet bubble in 2000 and smaller peaks in the global financial crisis of 2008, the Volcker experiment in the early 1980s, the first invasion of Iraq and other events in the early 1990s, and the European crisis in 2012. In other words, deep value events across markets and asset classes appear to cluster around times of bubbles or crashes, that is, times of exuberant richness or gloomy cheapness.

Exhibit 5 also shows the cumulative out-of-sample return to the overall deep value strategy. We see that the strategy appears to do well during periods of abounded deep value events. This intuitive result is confirmed in Exhibit 6, in which we regress the monthly return to deep value, $DVAL^i_{t+1}$, on the percentage of available trades meeting the deep value filter at the end of the previous month, $EVENTS^i_t$:

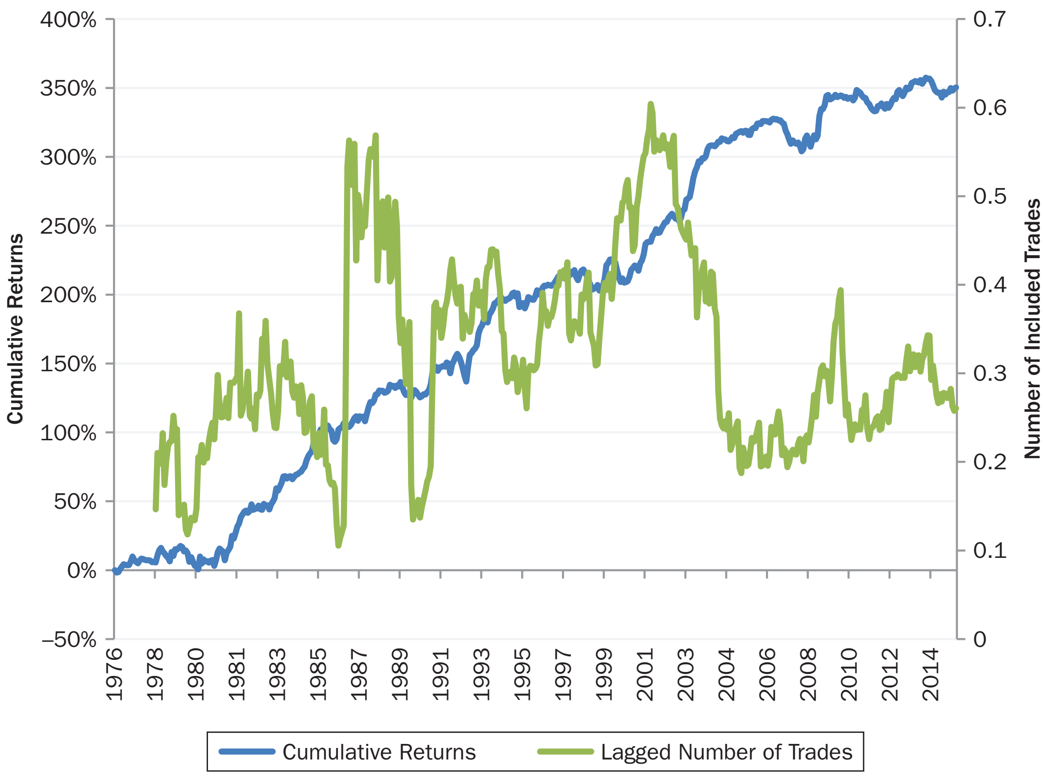
$$DVAL^i_{t+1} = \alpha + \beta\ EVENTS^i_t + \varepsilon^i_{t+1} \tag{11}$$

where *i* indicates either deep value among stocks, AA, or all assets. We see that the slope coefficient is significantly positive for all assets and SS, indicating that the deep value strategies earn higher average returns when there are many deep value events.

Exhibit 6 also considers how the volatility and Sharpe ratio (SR) or returns vary with the number of events. In Panel A, we regress one-year-ahead annualized returns, one-year-ahead volatility of returns, and the one-year-ahead annualized SR of the deep value strategy on the percentage of included value strategies. By design, the volatility rises with the number of events, given that our strategy deploys a greater risk budget in these instances, and it is not surprising that returns also rise as a result. However, because SR is the ratio of average excess returns to volatility, it is not obvious how SR changes when both the numerator and denominator rise. However, we see that the slope coefficient for the SR is significantly positive for all assets and for stocks for the deep value strategy. This finding indicates that, when many deep value events occur, the strategies have a high return even relative to their high risk. This is also somewhat intuitive, given that the strategies are more diversified in these periods

EXHIBIT 5

Deep Value Strategy: Cumulative Returns and Opportunity Set



NOTES: This exhibit depicts the cumulative returns of the deep value trading strategy overlaid against the percentage of available value trades that are included as deep value (SS industries and AA pairs).

EXHIBIT 6

Deep Value Returns and the Number of Deep Value Opportunities

Panel A: Regression of Level, Volatility, and Sharpe Ratio of Deep Value Returns on Number of Opportunities

	All Asset Portfolios			Stock Selection			Asset Allocation		
	Returns	Volatility	Sharpe	Returns	Volatility	Sharpe	Returns	Volatility	Sharpe
Estimate	0.5	0.1	4.3	0.2	0.0	2.1	0.2	0.2	2.5
(*t*-statistic)	(3.2)	(1.3)	(2.4)	(2.9)	(3.3)	(2.3)	(2.0)	(4.1)	(1.1)

Panel B: Level, Volatility, and Sharpe Ratio of Deep Value in Number of Opportunity Terciles

	All Asset Portfolios			Stock Selection			Asset Allocation		
	1	2	3	1	2	3	1	2	3
Returns	2.3%	6.3%	16.1%	0.6%	2.4%	6.4%	0.6%	4.0%	10.9%
Volatility	7.5%	9.4%	12.3%	4.1%	6.5%	8.0%	3.5%	5.1%	9.2%
SR	0.31	0.66	1.31	0.14	0.36	0.80	0.18	0.79	1.18

NOTES: This exhibit shows the relationship between the return and risk characteristics of the deep value strategy with the opportunity set. In Panel A, we regress the level, volatility, and Sharpe ratio of 12-month-ahead returns to deep value on the size of the opportunity set at the start of each period. The size of the opportunity set is measured by the number of included trades (SS industries or AA pairs) as a percentage of available trades (those meeting the 80th percentile filter for value spreads). In Panel B, we bucket the level, volatility, and Sharpe ratio of returns into terciles based on the opportunity set.

because a greater number of trades are included (although this greater diversification is partially offset by value trades being more correlated to each other during this period of wider value spreads).

In Panel B, we present a bucketing analysis of the returns, volatility, and SR of deep value returns relative to terciles of the percentage of available opportunities. We see that within SS, AA, and across all strategies, average returns, risk, and SRs all increase with the number of deep value opportunities. Furthermore, we see that the returns are positive in each group, illustrating that the rewards to deep value are not solely driven by the time periods in which opportunities abound—as also seen from the cumulative returns in Exhibit 5.

THE ECONOMIC FUNDAMENTALS OF DEEP VALUE

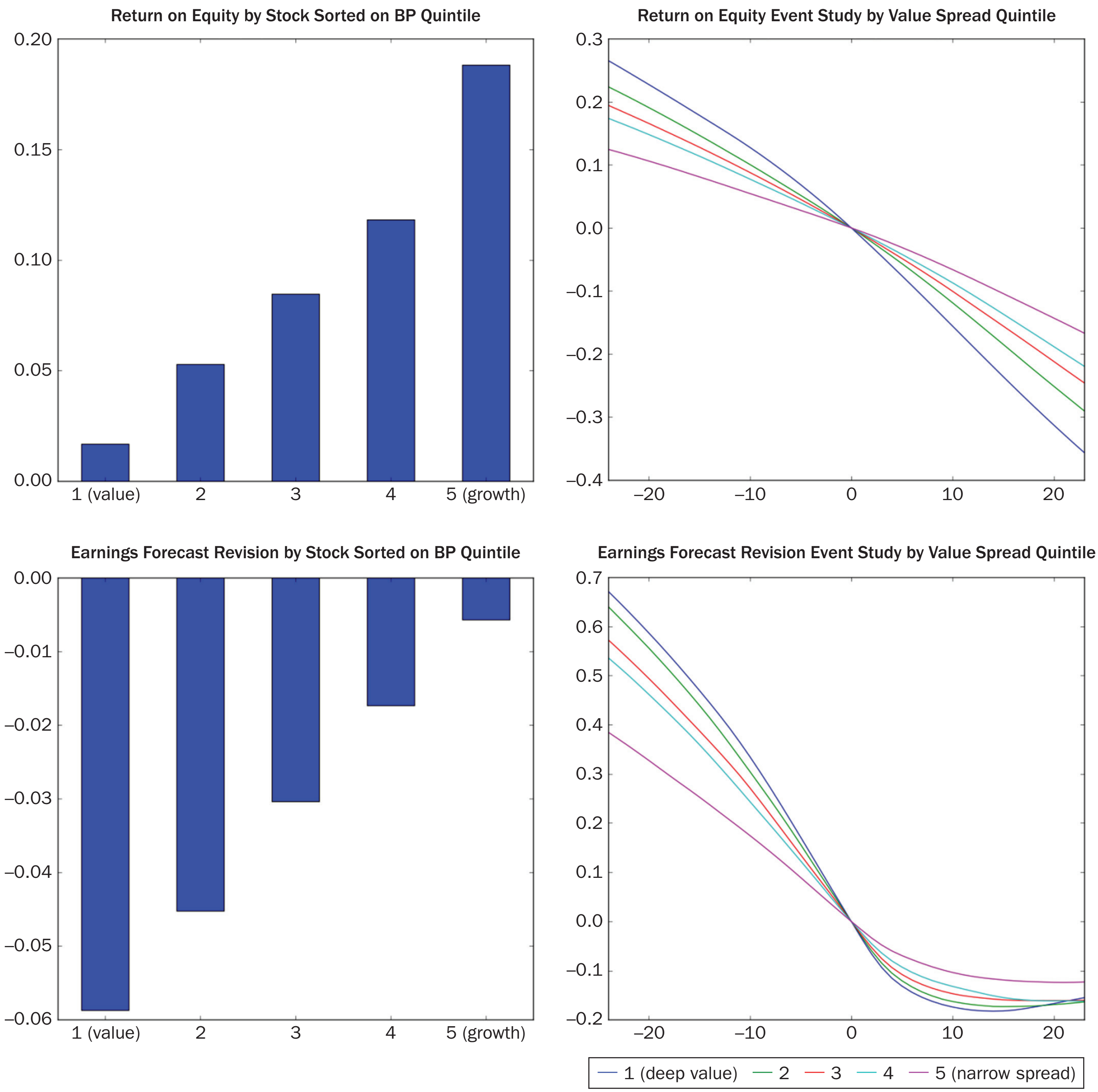
Having presented compelling evidence of deep value episodes being associated with higher future returns to value, using both in-sample and out-of-sample sorts, we next seek to analyze how the portfolio fundamentals evolve around deep value events. This has important relevance in the context of the theory section and Exhibit 1: Fundamental drivers of deep value episodes would be inconsistent with a potential theory of value (and deep value) being driven by noise in prices. Our previous analysis around clustering of deep value events and net losses accrued by companies becoming deep value buys hinted at a relationship with fundamentals. Here we study this relationship directly. We focus on SS because this is where we have in-depth data on both forecasted and realized earnings.

Exhibit 7 shows firms' realized earnings, measured as return on equity (income before extraordinary items divided by book value of equity, based on data from Compustat). The format is identical to Exhibit 3: The bar plot on the left analyzes the relationship of earning fundamentals and valuation ratios (i.e., the static relationship between value and earnings fundamentals), and the line plot on the right analyzes the evolution of value portfolio fundamentals in different value spread environments (i.e., dynamics in the relationship between value portfolios and earnings fundamentals). We see from the bar plot that value stocks are less profitable than growth stocks, as is well known (see, e.g., Cohen, Polk, and Vuolteenaho 2003).

More importantly, the line plot highlights the new result that the worse fundamentals of value stocks (or negative aggregate fundamentals for the long–short value portfolio) are meaningfully worse during deep value episodes. Specifically, for each value spread quintile, in each month, we compute the sum-product of the value portfolio weights and the stock-level returns on equity to derive a portfolio-level return on equity, which is cumulated and rescaled to a level of zero at event time zero. We see that the earnings of the value firms (the long positions in the value strategy) minus that of the growth firms (the short positions) deteriorate more than two years before portfolio formation, as seen from the downward-sloping cumulated earnings (to the left of 0 on the *x*-axis). Furthermore, this deterioration of earnings continues for more than two years after portfolio formation (as seen from the downward-sloping line to the right of 0). In addition to the deterioration of earnings being strongest for the deep value events, it is monotonic across the value spread buckets. Hence, part of the explanation for the large price discrepancy between value and growth stocks during deep value events is that prices rationally predict the future evolution of earnings.

We next turn to analyst forecast revisions. These are sourced from equity analyst earnings forecasts in the Thompson Reuters Institutional Brokers' Estimate System (IBES), and we track a standard earnings revisions ratio metric. This is a measure that tracks trends in analyst forecasts on a stock: Positive numbers indicate analysts becoming more bullish and a negative number that analysts are becoming more

EXHIBIT 7
Earnings Fundamentals of Deep Value



NOTES: This exhibit shows earnings fundamentals for stocks sorted by value quintile on the left and event studies of earnings fundamentals for value portfolios having different valuation spread quintiles on the right. The top panels show the annual return on equity (income before extraordinary items divided by book value of equity). The bottom panels shows the rolling three-month analyst earnings forecast revision ratio (up revisions minus down revisions divided by number of forecasters) from Thompson Reuters I/B/E/S.
Both event studies are cumulated.

bearish. Specifically, the measure is computed as a three-month moving average of the number of upward revisions in earnings forecasts minus the number of downward revisions in earnings forecasts divided by the total number of forecasters. The bar plot shows that value stocks face more negative revisions than growth stocks, on average, and forecasters tend to revise forecasts down more often than they revise them up for all groups (related to analysts' general overoptimism and their downward earnings adjustments as earnings announcements approach). The corresponding event study shows that the value portfolio faces negative revisions before portfolio formation (i.e., the revisions of the long positions minus those of the short positions is negative), and these negative revisions continue for about a year after portfolio formation. Interestingly, for deep value, these effects are stronger; additionally, we see a reversal a year after portfolio formation in which the revisions start to turn positive.

THE RISK DYNAMICS OF DEEP VALUE INVESTING

Exhibit 8 considers the risk of value portfolios (instead of the return shown in Exhibit 3). This is an important consideration in the context of the theory summarized in Exhibit 1; a relationship between deep value and the riskiness of value portfolios would lend support to rational theories of the value premium. As before, the left-hand side of the figure focuses on static relationships between company valuations and riskiness, and the right-hand side focuses on the dynamics of long–short value portfolios in deep value and other value spread regimes. The top-left bar plot in Panel A measures the full-sample market beta of stocks returns for each quintile, using three-day overlapping daily returns.[12] The corresponding bar plot for AA strategies is in Panel B. Overall, the results do not show a clear relationship between beta and valuations.

The top-right line plot shows how market betas of long–short value portfolios vary with the value spread over event time. Betas are once again computed using three-day overlapping daily returns. We see that the market beta of daily returns is slightly negative for all groups and is, if anything, slightly more negative for deep value. Hence, deep value investing in stocks appears to hedge market risk, which makes the returns to deep value all the more puzzling from the perspective of the CAPM model. Panel B shows a similar finding for other assets, although to a lesser extent.

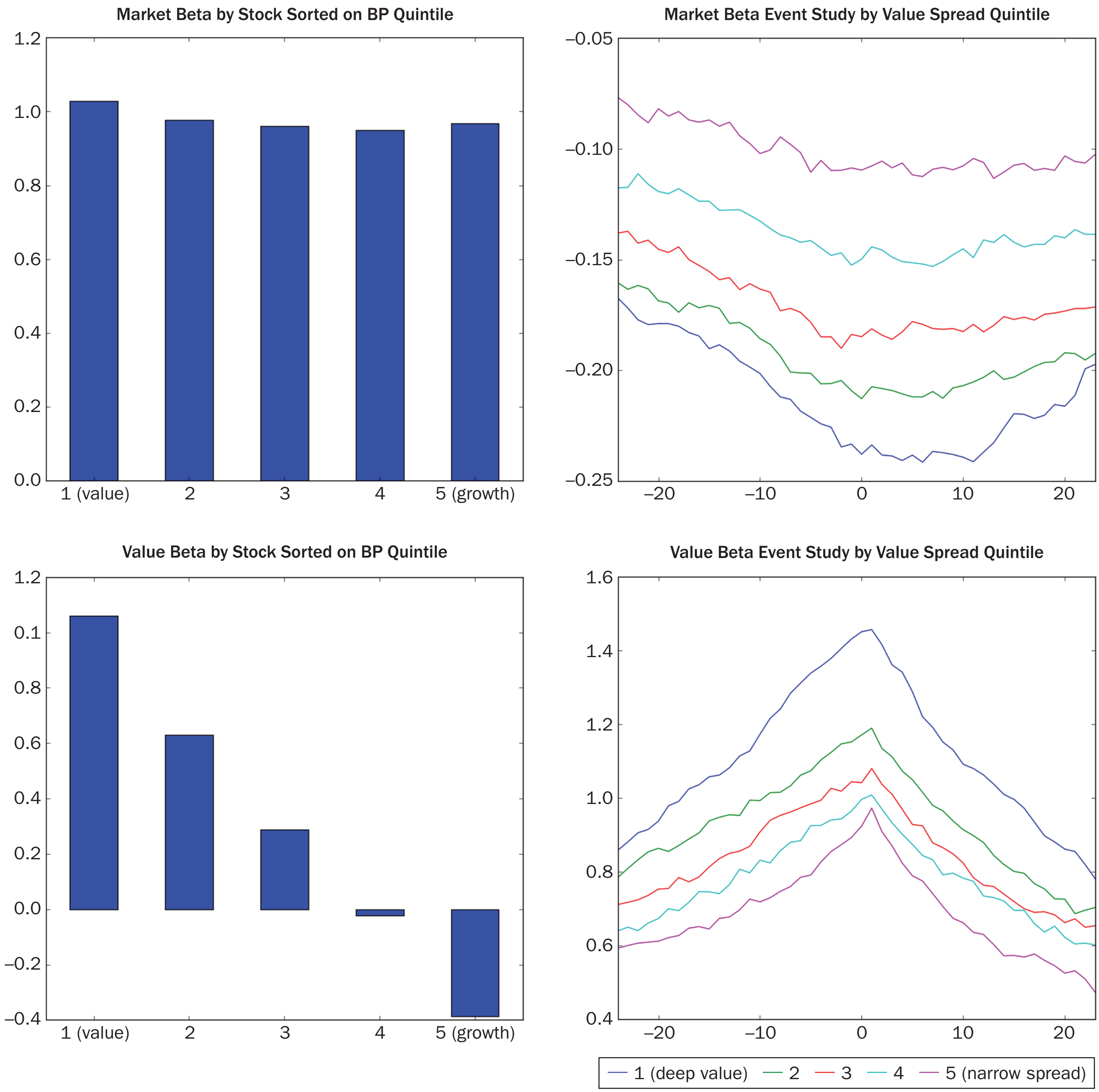
The second bar plot shows the loading of stock quintiles on a global value factor. The global value factor is defined separately for each SS region and asset class and is computed as the simple average return of all value strategies within that region or asset class. For example, the US SS value factor is the average of the return to value traded within each of the 68 industries in the United States. Of course, value stocks have a positive loading on the value factor, and growth stocks have a negative loading, and we see the same phenomenon for other assets in Panel B. The corresponding event-study line plot shows the dynamics of the value loadings for the long–short value strategy. These value loadings are naturally all positive, but, more interesting, the loading is highest for deep value, especially around the time of portfolio formation. Hence, to the extent that value investing is exposed to a rational risk premium, this risk is most severe for deep value, which can potentially explain the high returns to deep value. Although the greater return of deep value being partially explained by greater global value risk (but not greater market risk) does lend some support to rational theories, this explanation is partial at best, given the earlier evidence in

[12] As expected, stock betas are roughly 1 on average, but the average is not exactly 1 because we do a simple average of the results from industry-level sorts, rather than weighting by market capitalizations of different industries.

EXHIBIT 8

Risk Dynamics of Deep Value

Panel A: SS

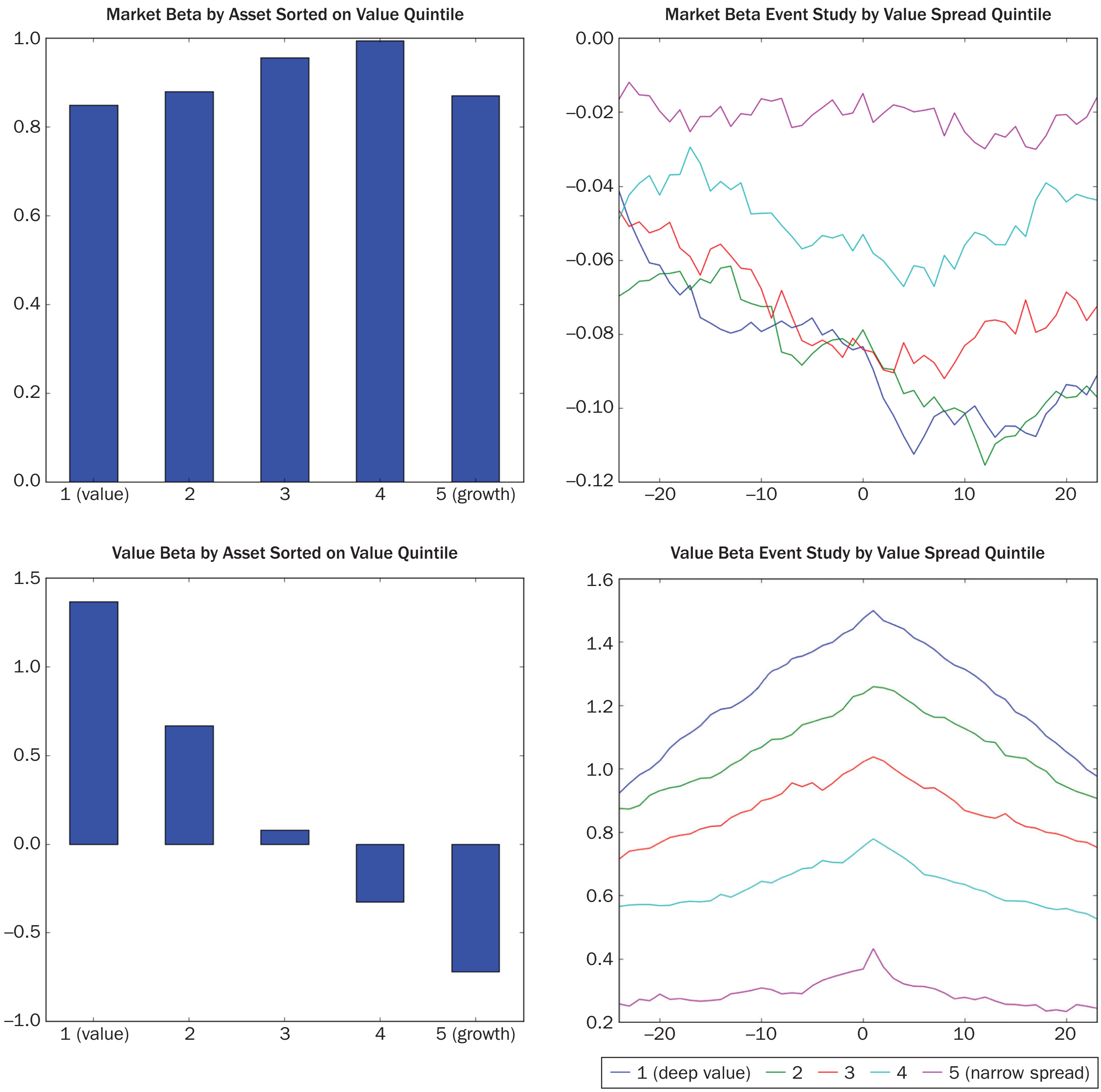


(continued)

EXHIBIT 8 *(continued)*

Risk Dynamics of Deep Value

Panel B: AA



NOTES: Panel A shows, on the left, bucket sorts of measures of risk of stocks of different valuation quintiles and, on the right, an event study tracking historical and future risk of value portfolios that have different levels of valuation spreads. Event studies are computed as in Exhibit 3. Two metrics of risk are considered: beta of returns to the market (top graphs) and beta of returns to a value benchmark (bottom graphs). Panel B reports the same for AA strategies. In SS, the value benchmark for each industry value strategy is the average return of all industry value strategies industries within the given region. For AA, the value benchmark for each asset pair value strategy is the average return for all pairs of value strategies within the given asset class.

Exhibit 4 that deep value has a significant alpha when controlling for other risk factors, including the standard value factor.

The Behavior of Investors and Arbitrageurs

Having ruled out a theory of value and deep value being driven by noise in prices and provided limited support for rational theories, we finally study a variety of different datasets documenting the behavior of investors and arbitrageurs in deep value episodes, seeking evidence for investor behavior being a potential driver of the value premium.

Sentiment for Value versus Growth Stocks: The Tone of News Stories

We first consider how investors feel about value versus growth stocks (i.e., the investor sentiment of value portfolios). Of course, sentiment is notoriously difficult to measure, but we can at least look at some proxies while acknowledging their limitations. First, note that analyst revisions themselves can be driven by a mixture of fundamental changes and sentiment. Hence, the negative analyst revisions for value stocks mentioned in the section on the economic fundamentals of deep value may also partly reflect negative sentiment.

As a more novel measure of sentiment, we consider the tone of news stories about value versus growth stocks. The data on news sentiment are sourced from RavenPack, and we track a metric of event sentiment score. This score ranges from 0 to 100 and is intended to capture the average sentiment (positive versus negative) of news stories about companies. A score of 50 reflects a neutral sentiment, a score greater than 50 reflects positive sentiment, and a score below 50 reflects negative sentiment. The bar plot in Exhibit 9 shows that the tone of news regarding value stocks tends to be less favorable than the tone in stories about growth stocks, on average.

The line plot in Exhibit 9 shows the evolution of the difference in tone of news about value versus growth stocks. We see that this measure of sentiment turns particularly negative leading into the time of portfolio formation, especially for deep value, and recovers to a more normal level in the year thereafter.

Demand Pressure: Do Investors Run When Stocks Get Cheap?

We next consider whether investors in fact act on this sentiment in terms of their buying and selling decisions. Exhibit 9 shows net buying of stocks: a measure of which types of stocks face buying or selling pressure.

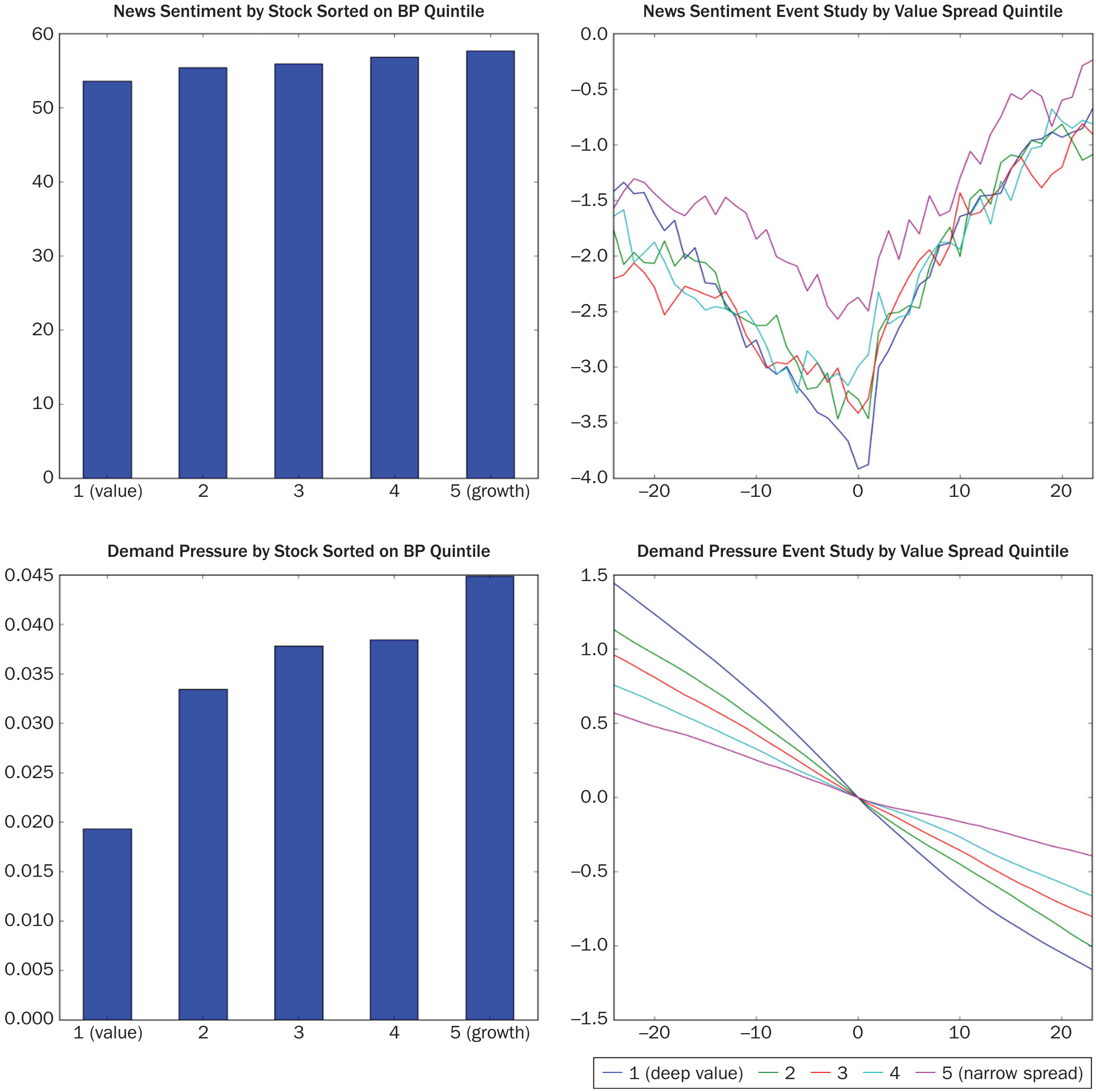
The bar plot shows the net buying for each stock, defined as dollar buys minus dollar sells divided by buys plus sells. Here, buys and sells are classified based on tick-level data using the Lee and Ready (1991) methodology as implemented by Chordia, Roll, and Subrahmanyam (2002, 2005, 2008).[13] We see that all groups of stocks experience more buying than selling on average, but the buying pressure is much stronger for growth stocks than for value stocks.

The line plot shows how the demand pressure for the long–short value portfolio evolves over time. We see that the value portfolio experiences net selling pressure in the sense that the net buying of the longs is smaller than the net buying of the shorts, which explains why all of the lines are decreasing in event time. Interestingly, the selling pressure in strongest for the deep value strategy, starting more than two years before portfolio formation and continuing for more than two years after. Hence, when value stocks become really cheap, some investors appear to run for

[13] We are grateful to Tarun Chordia for these data.

EXHIBIT 9

Sentiment and Demand Pressure of Deep Value



NOTES: The top panels show news sentiment for stocks sorted by value quintile on the left and event studies of cumulated news sentiment for value portfolios having different valuation spread quintiles on the right. The measure of news sentiment is the event sentiment score (ESS), provided by RavenPack. The ESS is a score between 0 and 100 that represents the average sentiment of news stories related to earnings, dividends, or revenues for a given company. The bottom panels show demand pressure for stocks sorted by value quintile on the left and event studies of cumulated demand pressure for value portfolios having different valuation spread quintiles on the right. The measure of demand pressure is dollar buys minus dollar sells divided by buys plus sells per stock, based on the Lee and Ready (1991) methodology.

the exits, consistent with the behavioral models and liquidity spirals (Brunnermeier and Pedersen 2009). For further evidence of investors running for the exists, see Mitchell, Pedersen, and Pulvino (2007) and Pedersen (2009).

What Do Investors (Over-)React To?

We have seen that value stocks face selling pressure relative to growth stocks, but what do selling investors react to? Are they reacting to past fundamentals or past returns? Answering this question will help us differentiate between two competing behavioral theories, as seen in Exhibit 1. To address this question, we regress demand pressure (measured as signed order flow) on past returns and past changes in fundamentals (measured as changes in return on equity). Owing to data availability for our demand pressure measure, these regressions are run for US stocks only.

The results are reported in the first three columns of Exhibit 10. We see in column 3 that demand pressure is driven by recent returns (within the past year) and long-term returns (over the past five years), but controlling for these effects, demand pressure is not driven by past fundamentals. In the regression in column 2, demand pressure is related to past fundamentals because past fundamentals and returns are correlated. This evidence is consistent with the theories of over-extrapolation of past returns but not overreaction to fundamentals.

Exhibit 10 also reports the evidence for how past returns and fundamentals predict returns (rather than demand pressure) in columns 4–6. Columns 4 and 6 show that recent returns predict future returns positively (the momentum effect), and long-term returns predict future returns negatively (as from DeBondt and Thaler 1985). In column 5, changes in fundamentals do not predict future returns, but when controlling for past price changes in column 6, short-term (and, especially, long-term) changes in fundamentals predict returns positively. This evidence is consistent with the idea that investors on average underreact to fundamentals (so good fundamentals predict positive returns, controlling for past returns) and overreact to past returns, leading to short-term momentum and eventual return reversal, thus creating a value effect.

EXHIBIT 10
What Do Investors (Over-)React To?

	1-Month-Ahead Demand Pressure			1-Month-Ahead Returns		
	Returns Only	ROE Only	Both	Returns Only	ROE Only	Both
Ret (2,12)	0.019		0.019	0.002		0.1%
(*t*-statistic)	(14.3)		(13.2)	(1.5)		(1.2)
Ret (13,60)	0.018		0.018	–0.003		–0.003
(*t*-statistic)	(17.4)		(14.4)	(–3.9)		(–3.9)
ΔROE (2,12)		0.002	0.000		0.000	0.000
(*t*-statistic)		(7.4)	(0.1)		(0.1)	(1.3)
ΔROE (13,60)		0.012	0.001		0.000	0.002
(*t*-statistic)		(13.1)	(1.0)		(–0.4)	(2.6)
R^2	1.67%	0.12%	1.58%	0.03%	0.00%	0.03%

NOTES: This exhibit shows the results of regressing the monthly signed order flow (the column labeled 1-Month-Ahead Demand Pressure) or the future one-month return (1-Month-Ahead Return) on past returns and past fundamentals. Specifically, the independent variables are the past returns over the last 2 to 12 months (Ret (2,12)), the returns over the past 13 through 60 months (Ret (13,60)), and changes in fundamentals measured as changes in return-on-equity over the same time horizons (ΔROE (2,12) and ΔROE (13,60)). Demand pressure is capture by signed order flow, defined as dollar buys minus dollar sells divided by buys plus sells per stock based on the Lee and Ready (1991) methodology. Regressions are run with time fixed effects with standard errors adjusted using Newey and West (1987).

The Limits of Value Arbitrage: Transaction Costs, Shorting Costs, and Arbitrage Risk

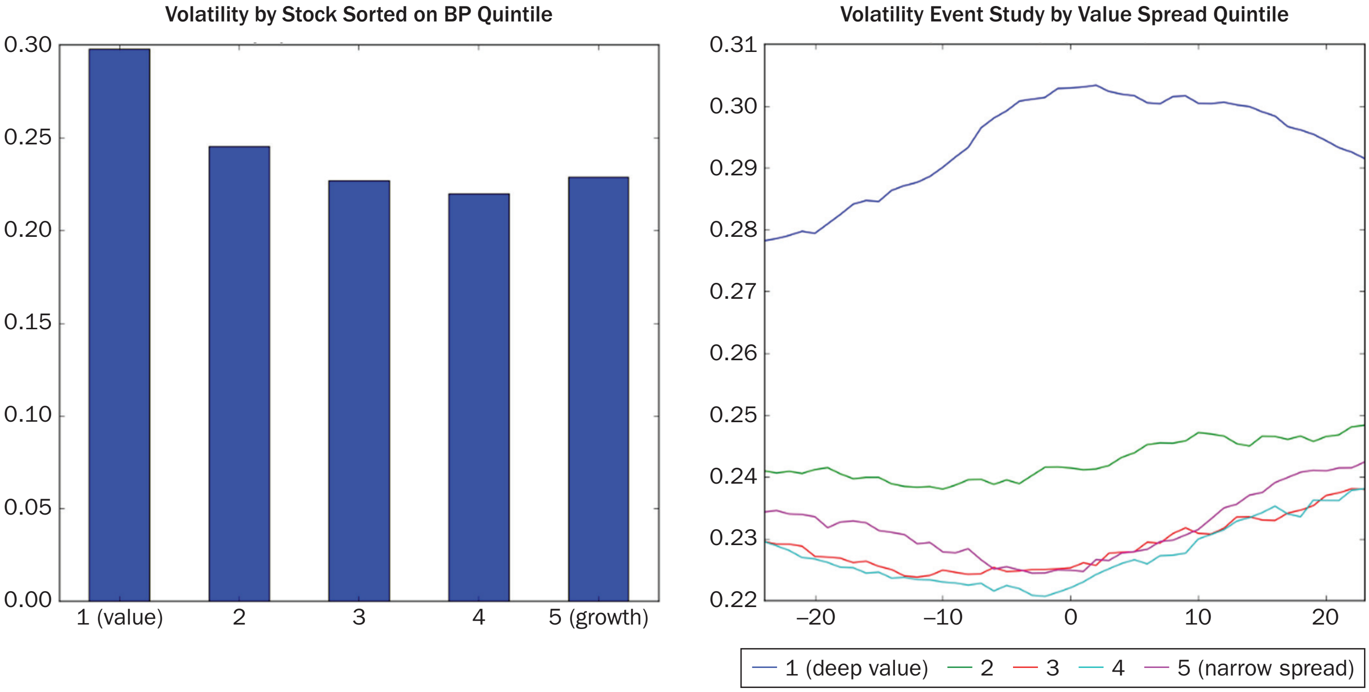
Of course, for every seller there is a buyer, and behavioral models suggest that arbitrageurs take the other side when behavioral investors run for the exits. However, arbitrageurs only do so to a limited extent if costs and risks are associated with the trade, which would provide further evidence that behavioral price effects can explain the high returns to deep value. Exhibit 11 presents evidence consistent with this hypothesis.

EXHIBIT 11

The Limits of Deep Value Arbitrage

(continued)

EXHIBIT 11 *(continued)*
The Limits of Deep Value Arbitrage



NOTES: This exhibit shows three measures of limits of arbitrage for stocks sorted by value quintile on the left and corresponding event studies on the right. The first row of graphics shows the bid–ask spread as a percentage of the price of stocks from CRSP. The event study shows the average of bid–ask spreads for the long and short side of the portfolio. The second row shows the shorting cost measured as the simple average fee of monthly stock borrows from hedge funds from Data Explorers. The event study represents the shorting costs of the short (expensive) side of the portfolio only. The third row shows the volatility of returns of stocks, computed from daily returns of stocks on a rolling monthly basis. The event study shows the volatility of the long–short value portfolio.

The top-left bar plot shows that bid–ask spreads are greater for value stocks than for growth stocks, on average. Hence, models of liquidity and liquidity risk could potentially explain part of the value effect (Amihud and Mendelson 1986; Acharya and Pedersen 2005). Bid–ask data are sourced from CRSP; therefore, this analysis is computed for US SS value only.

Furthermore, transaction costs pose a limit to arbitrage, and we are interested in whether transaction costs are particularly severe during deep value events as we examine the top-right line plot of Exhibit 11. This event study shows the average bid–ask spreads across the long and short sides of the value strategy (rather than the difference in longs versus shorts as in the other event studies), reflecting the costs incurred by an arbitrageur trading on the value strategy. We see that the bid–ask spread is much higher during deep value events, especially around the time of portfolio formation, consistent with the idea of limits of arbitrage.

The next set of plots in Exhibit 11 show the short-selling fees, for which we use the simple average short fee from Data Explorers. The bar plot shows that, on average, shorting costs are similar for value and growth stocks, but both sides face higher shorting costs than for average stocks (those with B/P ratios in the second through fourth quintile). Because the value arbitrageur only shorts the expensive growth stocks, the event study shows the evolution of this relevant cost of arbitrage. We see that the shorting cost for growth stocks is particularly high during deep value events: both leading into the event and for more than a year after portfolio formation, a period during which the shorts are typically maintained. Hence, shorting costs present another limit of arbitrage for (deep) value investing.

Finally, the third row of plots considers volatility, measured simply as the annualized standard deviation of returns. The bar plot, which tracks the realized volatility of three-day overlapping daily returns for stocks in different value quintiles, shows that value stocks tend to realize higher volatility on average than do growth stocks. The line chart tracks the realized volatility of three-day overlapping daily returns of long short-value portfolios. Here, we see that value portfolios experience significantly greater volatility during deep value episodes than on average. Moreover, volatility increases meaningfully into the portfolio formation period and then persists at a high level for up to two years after. In other words, investors looking to take advantage of deep value opportunities must bear greater volatility risk, presenting another potential limit to arbitrage. Said differently, deep value is not as attractive when considering its SR rather than its expected return. More broadly, deep value investors face the risk that they cannot stay solvent until the market turns around (Shleifer and Vishny 1997).

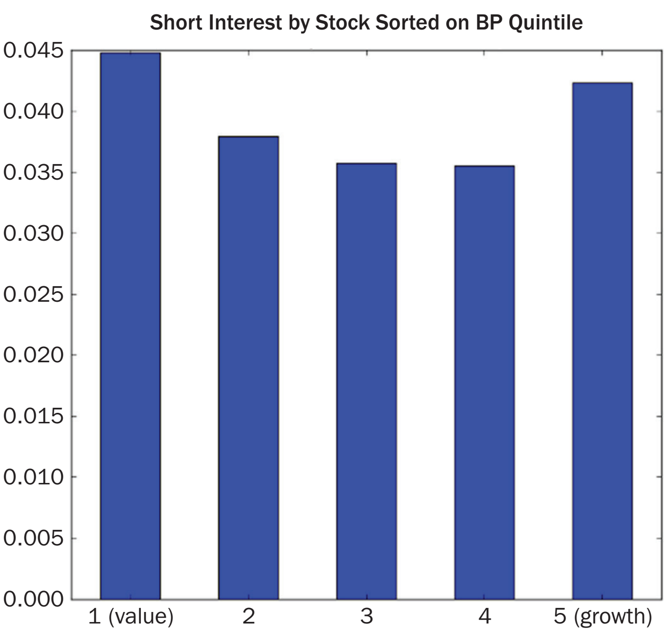
In summary, arbitrage is limited by elevated transaction cost, short-selling fees, and volatility. Arbitrageurs also face other challenges such as the clustering of deep value opportunities that we documented earlier.

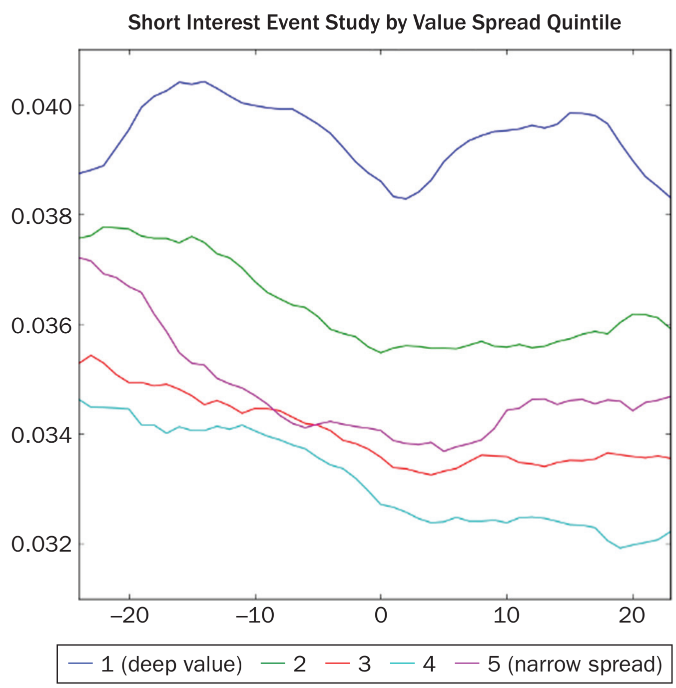
Arbitrage Activity: Short-Sellers, Share Buybacks, and Takeovers

Finally, we look at whether arbitrageurs appear to trade on value and whether they do so to a larger extent during deep value events. Exhibit 12 first considers short interest, reflecting an element of arbitrage that is more easily observable in the data. The specific metric plotted is the short interest divided by the number of shares outstanding, which is provided for US stocks by FT interactive. The bar plot shows that, perhaps surprisingly, short interest is slightly higher for value stocks than for growth

EXHIBIT 12

Deep Value Arbitrage Activity

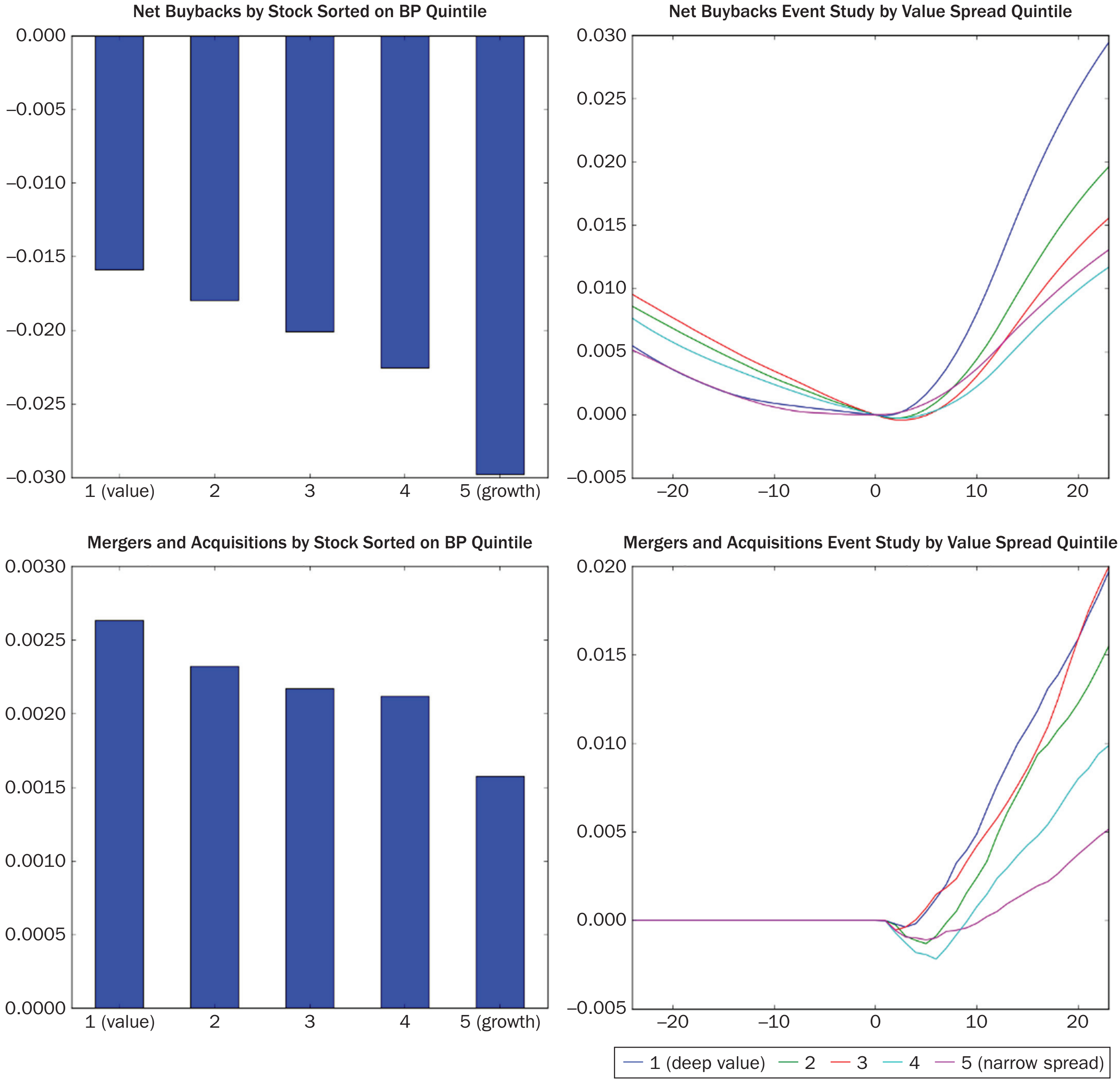




(continued)

EXHIBIT 12 *(continued)*

Deep Value Arbitrage Activity



NOTES: This exhibit shows three measures of arbitrage acitivity for stocks sorted by value quintile on the left and event studies of measures of arbitrage activity for value portfolios having different valuation spread quintiles on the right. The first row shows short interest data from Compustat normalized by the number of shares outstanding. The event study is shown for the short side of the portfolio only. The second row shows net buybacks, as measured by the negated monthly change in shares outstanding, provided by Compustat. The bar chart, which shows the average rate of buybacks for different valuation quintiles, has negative values, consistent with issuance on average. The event study tracks cumulative buybacks for the valuation portfolio (difference between long side and short side). The third row tracks acquisitions of stocks using CRSP delisting codes (in the left graphic, we lag book-to-price ratios by six months before sorting in an attempt to capture preannouncement valuations). In the event study, we show the cumulative acquisitions in the long–short value portfolio (the difference between long side and short side).

stocks, although both value and growth stocks have higher short interest than other stocks. For the event study, we focus on the short interest of growth stocks because that should track the shorting activity of value-focused arbitrageurs. The findings are intuitive: Short interest for growth stocks is larger during deep value events and is elevated for several years before and after the portfolio formation time. Interestingly, we also see a small dip in short interest just after event time zero, albeit to a level that is still high; this dip could reflect some arbitrageurs being forced to reduce their positions owing to risk management, lack of capital owing to losses, shorting costs, lack of short availability (perhaps even forced closure of certain short positions), or other effects.

We next consider whether firms act as arbitrageurs of last resort in their decisions to issue, repurchase, or perform takeovers. We first consider net buybacks, defined as the negated percentage change in shares outstanding. The bar plot shows that all values are negative on average, indicating that companies tend to issue shares on average and that growth companies tend to issue more shares than value companies. Moreover, after a deep value event, we see that the cheap value firms have much larger net buybacks than the growth stocks. Over the two years after portfolio formation, the difference is 3%, which means that the cheap firms have repurchased 3% of their own shares, assuming that the growth firms have zero net buybacks. In reality, we see that, although the management of both value stocks and growth stocks tends to issue stocks, the issuance is much more aggressive for growth stocks. Over a two-year horizon, we see roughly 6% net issuance for growth stocks, compared to 3% for value stocks.

Last, we look at a firm's propensity to being bought depending on its valuation. We use the CRSP dataset here, so the analysis is done for US stocks only, and a buyback is a binary event at a stock level. Specifically, we look for cases in which a stock is delisted with a delisting code of 300 or 400. For the purpose of the bar chart, we lag the valuations used to form quintiles by six months, in an attempt to capture preannouncement valuations. We believe this adjustment is prudent, given the tendency of takeover targets to dramatically change price after the announcement of the takeover, potentially altering their valuation profile relative to when the takeover was announced.

The bar plot shows that buyouts are much more likely for value stocks than for growth stocks. Specifically, the chance that a value stock is bought in any given month is 0.26%, whereas the corresponding number for growth stocks is only 0.15%. The event study shows the cumulative probability of being taken over after the time of portfolio formation for value stocks, minus the cumulative probability for the growth stocks (here we do not lag because the time dynamics of future buyouts of current value stocks is naturally captured by an event study). The lines start at zero because any firms included in the portfolio at formation time must necessarily not have been bought prior to that time.

We see that, over a two-year period, all the lines have increased, consistent with the evidence from the bar plot that value stocks are more likely to be taken over. Interestingly, the total increase is largest for the deep value events and smallest for the narrow spread portfolios, suggesting that acquirers act as arbitrageurs of last resort during deep value events. Interestingly, the lines tend to decrease initially, for a period of roughly six months, before increasing, indicating a propensity for growth stocks to be bought more than value stocks immediately after portfolio formation. In all likelihood, these are stocks for which the takeover announcement was made prior to portfolio formation and, therefore, for which the takeover premium has already been reflected in prices. In other words, if a stock was the target of a merger announced the month before portfolio formation, it might be expensive relative to its own book value as of time zero and, hence, included in the growth portfolio. If the takeover is completed three months after time zero, it would be reflected as a negative in the line chart.

CONCLUSION: DEEP VALUE—RISK, (ANTI-) BUBBLES, OR NOISE?

We shed new light on what happens during deep value episodes in which valuation differences rise between cheap and expensive securities. These episodes can be driven by very low prices of value securities, very high prices of expensive securities, or some combination of the two. We study the causes and consequences of these extreme price differences. Are they rational compensation for differences in risk? Or do irrational fear and greed lead to fire sale prices of value securities and high bubble prices of expensive securities? We use a vast amount of data on prices, fundamentals, earnings, order flow, sentiment, arbitrage cost, and arbitrage activity to answer these questions. Our results indicate that deep value reflects a combination of rational price moves and irrational fear and greed. Deep value episodes tend to happen when investors overreact to past returns related to changing economic fundamentals, and arbitrage activity that counters this sentiment-driven overreaction is limited by costs and risks, leading to price dislocations that are partially reversed in the future.

In summary, we provide a method to identify bubbles among expensive securities and anti-bubbles among cheap securities. We show how these bubbles and anti-bubbles are inflated by demand pressure driven by past returns, and partially deflated by arbitrage.

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