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IDIOSYNCRATIC RISK AND WHEN TO TILT TOWARD VALUE

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While the outperformance of value relative to growth portfolios has been well established, there is still debate over whether this outperformance is the result of a systematic risk factor or a behavioral tendency. The distinction is crucial to determining the expected returns of value- and growth-tilted portfolios. We find that when idiosyncratic volatility—the key arbitrage portfolio holding cost—increases, the outperformance of value correspondingly increases. Conversely, when idiosyncratic volatility is low, the outperformance is reduced. This is consistent with a behavioral explanation and has important ramifications for the timing of value tilts employed by a portfolio manager.

The distinction between growth and value stocks has a long and storied history in the U.S. stock market. Practitioner standards by Graham and Dodd (1934) advocate the investment in securities valued below a latent intrinsic value, and academic work by Fama and French (1992) argue that the spread between value and growth firms is a proxy for fundamental systematic factors affecting securities. Studies by Lakonishok *et al.* (1994) and Hwang and Rubesam (2013) find that while value firms outperform growth firms, the explanation behind this outperformance is behavioral rather than reflective of fundamental risk. This distinction—whether the value–growth spread is fundamentally or behaviorally driven—is of considerable relevance to portfolio managers. Return spreads that are behavioral in nature can potentially be exploited by enterprising traders for abnormal profit even on a risk-adjusted basis.

For example, Lakonishok *et al.* (1994) find that investors use variables such as growth in sales, earnings, and various accounting multiples to identify poorly performing firms, and then forecast that sub-par performance too far into the future. The result of this behavioral explanation is that the prices of these firms drop too far (increasing their book-to-market ratio), and subsequently outperform. Growth stocks, or glamour stocks, exhibit the mirror image of this effect,

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in that their positive recent performance is overforecast, resulting in too-high prices (and low book-to-market ratios), and leading to subsequent underperformance. Enterprising traders can take advantage of this mean-reverting behavior.

But the typically positive value premium is a well-known phenomenon. How could such systematic, behaviorally-driven errors continue? One would expect arbitragers to eliminate such an obvious profit-making opportunity. The answer may lie in the holding costs associated with trying to implement the arbitrage trade. Shleifer and Vishny (1997) construct a model in which professional arbitragers are less effective in uncertain circumstances—in particular when prices are significantly different than their intrinsic values, and in high-volatility environments. They argue that both systematic and idiosyncratic volatility matter, and that idiosyncratic volatility may even matter more. Pontiff (2006) takes this further, arguing that idiosyncratic risk is the *single largest cost faced by arbitragers*. Phalippou (2008) finds that the value premium (defined simply as the return difference between portfolios of high and low book-to-market stocks) is largely concentrated in stocks owned primarily by individual investors. For stocks primarily owned by institutions, the value premium is largely nonexistent. Interestingly, in that article there is a strong negative association between institutional ownership and idiosyncratic risk (see p. 43—stocks in the lowest decile of institutional ownership had idiosyncratic volatility almost 10 times as high as those in the highest decile). Asness *et al.* (2015) suggest that investors may neglect simple investing styles such as value for several reasons, including "aversion to leverage, shorting, and/or derivatives" (see p. 56). This aversion may well be cost dependent.

The behavioral literature therefore suggests that the value premium should indeed persist, at least when the limits to arbitrage are reached—which Pontiff (2006) suggests should be in high idiosyncratic risk environments. The idiosyncratic risk environment fluctuates substantially through time. This would suggest that practitioners may benefit in tilting their portfolios toward value when idiosyncratic volatility is relatively high. This high idiosyncratic volatility limits the ability of arbitragers, at least until the environment returns to a more typical situation.[1] Bali *et al.* (2019) find idiosyncratic volatility at the firm level to be the driver behind persistent stock underperformance in a different setting. In particular, they find that when unusual news events affect a firm, high idiosyncratic volatility limits the ability of pessimistic investors to short sell the stock. This creates an environment such as that described in Miller (1977), in which only optimistic investors participate, driving up prices, and down subsequent returns.

In this paper, we test the relationship between idiosyncratic volatility and value outperformance, which may have important ramifications for active portfolio managers. Such managers often "tilt" their portfolios toward growth or value depending on the market environment, in hopes of outperforming the market in the future. Constraints on arbitragers in the form of idiosyncratic risk may provide a trading opportunity that could be quite valuable to such managers. And since arbitrage is limited, this relationship may be persistent as well.

1 Data

We collect our data from several sources. First, we collect monthly data on the total return to the Russell 1000 Value and Growth indices from Bloomberg. These are Bloomberg tickers "RU10VATR Index" and "RU10GRTR Index" for value and growth, respectively. Coverage for these indices begin in February, 1979, so we begin our data then, and all data is collected through

December 2018. We collect the Fama–French value factor high minus low (HML) from Wharton Research Data Services (WRDS) for the same time period.

Having two different indices representing our value trade significantly aids the robustness of the analysis. What is deemed "value" by academics and investors can vary, although all parties are trying to capture the same broad notion. The Russell indices use the book-to-market ratio to identify value stocks, and I/B/E/S medium-term growth forecasts along with the historical growth of sales-per-share over last five years to identify growth stocks. It is therefore possible for an individual stock to have both growth and value characteristics.[2] By comparison, the dividing line between growth and value is more clearly defined in the Fama–French methodology. Value is determined by book-to-market values of stocks, after having partitioned them by size (into two categories—larger and smaller than the median NYSE individual stock market capitalization).

To construct our forward-looking Russell index data, we form a long–short portfolio. For a given month, we compute the difference between the Russell 1000 Value and Growth indices. Denote this difference RVMG (Russell Value Minus Growth). This is analogous with HML, which constructs a high book-to-market portfolio return minus a low book-to-market return (see Fama and French (1992) for a detailed description of the construction of this factor). With these return differentials in hand, we then compute a forward-looking continuously compounded return for one-, two-, and three-year horizons. Prior work has suggested that forecasting intermediate-term return horizons of five to seven years is more effective than short-term horizons (see, for example Campbell and Shiller, 1988, 1998). While our roughly 40-year data set makes five- to seven-year forecast horizons a challenge, we opt for a slightly shorter definition of "intermediate" as one-, two-, and three-year horizons. This is a very conservative approach, in that these shorter horizons are likely a bit less predictable than the longer horizons used in previous studies. We compute these forward-looking returns for the RVMG and HML as

$$
\begin{aligned}
F1\_\text{RVMG}_t &= \sum_{k=1}^{12} \ln(1+\text{RVMG}_{t+k})\\
F2\_\text{RVMG}_t &= \sum_{k=1}^{24} \ln(1+\text{RVMG}_{t+k})\\
F3\_\text{RVMG}_t &= \sum_{k=1}^{36} \ln(1+\text{RVMG}_{t+k})\\
F1\_\text{HML}_t &= \sum_{k=1}^{12} \ln(1+\text{HML}_{t+k})\\
F2\_\text{HML}_t &= \sum_{k=1}^{24} \ln(1+\text{HML}_{t+k})\\
F3\_\text{HML}_t &= \sum_{k=1}^{36} \ln(1+\text{HML}_{t+k})
\end{aligned}
\tag{1}
$$

where t is the time index, and t and k are monthly indices.

There are several potential methods available to capture the idiosyncratic volatility environment. We follow the beta-free estimation procedure of Campbell *et al.* (2001) to estimate the monthly average of idiosyncratic volatility for the U.S. stock market. To compute this measure, we collect daily trading data for all publicly traded stocks in the United States from the Center for Research in Securities Prices (CRSP). Using the daily data, we then compute estimates for latent average monthly idiosyncratic volatility in the market. We follow recent literature in including only common stocks traded on the NYSE, AMEX, and NASDAQ with share prices equal to or greater than $3 per share. For delisted firms, we use the delisting return field provided in CRSP. The resulting procedure employs over 43 million firm-days to estimate the monthly average volatility series for our February 1979 to December 2018 time period.

Let R_{jit} be the excess return of firm j, in industry i, at time t.[3] Furthermore, let $R_{it} = \sum_{j \in i} w_{jit} R_{jit}$ be the excess return of industry i during time t, and let $R_{mt} = \sum_i w_{it} R_{it}$ be the excess return to the market. w_{jit} is the (market cap determined) weight of firm j in industry i at time t, while w_{it} is the (market cap determined) weight of industry i in the market at time t. Following Campbell *et al.* (2001), we estimate month t market volatility from daily data as

$$\mathrm{MKT}_t = \sum_{s \in t} (R_{ms} - \mu_{mt})^2 \tag{2}$$

where μ_{mt} is the mean daily market return over month t, and s indexes the days during month t. To determine average idiosyncratic (firm-specific) volatility in the market, decompose the daily excess firm return as

$$R_{jis} = R_{is} + \theta_{jis} \tag{3}$$

where $s \in t$. Then the monthly idiosyncratic volatility for firm j in industry I at time t may be estimated as

$$\hat{\sigma}^2_{jit} = \sum_{s \in t} \theta^2_{jis}. \tag{4}$$

We may then aggregate the weighted average of the idiosyncratic volatilities in a given industry i as

$$\hat{\sigma}^2_{it} = \sum_{s \in t} w_{jit} \hat{\sigma}^2_{jit} \tag{5}$$

Finally, we compute the average idiosyncratic volatility in the market for month t as

$$\mathrm{FIRM}_t = \sum_i w_{it} \hat{\sigma}^2_{it}. \tag{6}$$

See Campbell *et al.* (2001) for a more detailed description of the computational procedure.

FIRM and *MKT* provide an interesting contrast. While both variables are proxies for different measures of volatility, the idiosyncratic risk proxied by *FIRM* is a holding cost for arbitragers. *MKT* is not. If arbitrage holding costs are preventing arbitragers from correcting known behavioral biases in the market, we expect abnormal value returns to be tied to *FIRM*, but not *MKT*.

There are many variables that an investor may use to attempt to forecast value–growth spreads, though few variables have reliably demonstrated forecasting power in the academic literature. Campbell and Shiller (1988) find that using averages of past earnings is effective in forecasting future market returns. This finding has evolved into the widespread use of the CAPE (Cyclically Adjusted Price to Earnings) ratio for market forecasts.[4] We collect the monthly CAPE ratio for our full-time period from Robert Shiller's website and denote this variable *CAPE*.[5] The slope of the Treasury yield curve has been demonstrated to forecast the performance of the U.S. economy (Estrella and Mishkin, 1998) and the U.S. stock market (Resnick and Shoesmith, 2002). We define the slope of the yield curve as the difference between the 10-year and 1-year Treasury yield and include this explanatory variable in our analysis. Treasury yields are gathered from the Federal Reserve Economic Data compiled by the St. Louis Fed (available at https://fred.stlouisfed.org) and denoted *YIELD_SLOPE*. While the academic research for CAPE supports only the forecast of market returns (rather than value–growth spreads), conversations with portfolio managers indicate that this variable is closely watched by practitioners making value versus growth investment decisions. Therefore, to be conservative we include both variables as controls in our analysis.

Table 1 Summary Statistics.

Variable	Mean	Std. Dev	25th Percentile	Median	75th Percentile	*N*
Panel A						
F1_RVMG	−0.004	0.106	−0.115	−0.009	0.047	468
F2_RVMG	−0.002	0.150	−0.085	−0.008	0.089	456
F3_RVMG	0.001	0.171	−0.114	−0.014	0.116	444
F1_HML	0.025	0.124	−0.065	0.029	0.100	468
F2_HML	0.057	0.170	−0.053	0.063	0.162	456
F3_HML	0.089	0.181	−0.045	0.075	0.202	444
FIRM	0.078	0.058	0.046	0.069	0.083	479
MKT	0.028	0.054	0.008	0.014	0.027	479
CAPE	21.765	8.668	15.301	21.784	26.587	479
YIELD_SLOPE	1.290	1.163	0.480	1.450	2.160	479
	F1_RVMG	*F2_RVMG*	*F3_RVMG*	*F1_HML*	*F2_HML*	*F3_HML*
Panel B						
F1_RVMG						
F2_RVMG	0.708	1				
F3_RVMG	0.489	0.787	1			
F1_HML	0.899	0.638	0.404	1		
F2_HML	0.638	0.914	0.692	0.693	1	
F3_HML	0.400	0.071	0.901	0.433	0.761	1

Descriptive statistics for our variables are given in Table 1. Interestingly, while the forward-looking HML derived variables are all positive and significant at the 1% level, that is not true of the Russell 1000-derived variables. However, their standard deviations are of similar magnitude, though the HML variables are slightly higher, primarily due to greater upside variation. The correlation (seen in Panel B) between the Russell- and HML-derived forward-looking variables is about 90% when the variables are compared at the same horizons (for example, *F2_RVMG* and *F2_HML* have a correlation of 91.4%).

The volatility variables, CAPE, and Treasury yield slopes are in line with prior literature and expectations. Idiosyncratic volatility (*FIRM*) is on average more than 2.7 times higher than market volatility (*MKT*). The mean level of CAPE is over 21. This is a bit higher than the mean reported in many CAPE studies, and is a direct result of the time period of our data—many of those studies use data back to the late 1800s, and CAPE has been higher in recent decades. The slope of the yield curve is positive, on average about 130 basis points separate the 1-year and 10-year Treasury yields.

2 Methodology

Our analysis of the relationship between idiosyncratic risk and subsequent value–growth returns is a relatively straightforward regression analysis. Specifically, we estimate regressions of the form

$$Forward\_Returns_t = \alpha + \beta_1 FIRM_t + \beta(CONTROLS_t) + \varepsilon_t \quad (7)$$

where *Forward_Returns* ϵ {*F1_RVMG, F2_RVMG, F3_RVMG, F1_HML, F2_HML, F3_HML*} and CONTROLS ϵ {*CAPE, YIELD_SLOPE*}. Importantly, note that we will be estimating the association between *FIRM*, the controls, and exclusively forward-looking returns (there is no time t information in $Forward\_Returns_t$, they are constructed with time $t+1$ to time $t+n$ returns, where n is the forward-looking horizon, in months.). Statistical inference is a challenge in this setup, as the dependent variables are constructed in such a way that there is significant serial correlation among them. Therefore, we pay particular attention to an appropriate bandwidth for our Newey–West estimators of the regression standard errors (see Newey and West, 1987).[6] Specifically, when we estimate our regressions with two-year forward returns, we will use a Newey–West bandwidth of 24 months. When we estimate our regressions with three-year forward returns, we will use a Newey–West bandwidth of 36 months. These large bandwidths notably lower the statistical power of our tests, but provide us with a conservative basis for our hypothesis tests—which is appropriate, given the serial correlation built into our model.[7]

Our methodology contrasts with that of Gulen *et al.* (2011). They find a relationship between the outperformance of value portfolio deciles relative to growth deciles (delineated solely by differences in book-to-market values) and conditional volatilities of those portfolios in the Markov switching framework of Perez-Quiros and Timmermann (2000). However, our methodology offers some noteworthy advantages over that framework. While Gulen *et al.* (2011) find significant time variation in the value–growth spread as we do here, they find almost nonexistent out-of-sample predictability of the relationship. A likely culprit for this result is the large number of parameters necessary for the estimation of Markov switching models. By employing a simple, linear model in Equation (7), we dramatically reduce the number of required estimated parameters relative to that approach. Furthermore, by including the idiosyncratic volatility environment

Table 2 Explaining the Value–Growth Spread.

	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	−0.060	−0.002	−0.099	−0.001	−0.110
	(0.587)	(0.969)	(0.015)**	(0.978)	(0.248)
CAPE	0.050				−0.000
	(0.617)				(0.897)
YIELD_SLOPE		0.002			0.013
		(0.917)			(0.513)
FIRM			1.241**		1.316**
			(0.016)		(0.017)
MKT				0.068	
				(0.830)	
Observations	448	448	448	448	448
R-squared	0.021	0.000	0.184	0.001	0.192

The dependent variable in each regression is the three-year ahead value–growth spread, measured as the accumulated difference between the return to a long–short Russell Value—Russell Growth portfolio.
Note: Parenthetical values are Newey–West adjusted p-values with using a 36-month bandwidth.

specifically into the model via *FIRM*, we attempt to identify a likely basis for the persistence of the value–growth spread—higher arbitrage costs.

Table 2 provides our first set of results, with several regressions of the form in Equation (7). Our dependent variable for all regressions in the table is *F3_RVMG*. In Models 1 and 2, we regress this three-year ahead looking spread variable on *CAPE* and the slope of the yield curve, respectively. Individually, neither of these variables have predictive value at any conventional statistical level. Model 3 provides a striking contrast. The coefficient on *FIRM* is statistically significant, and its positivity indicates that when idiosyncratic volatility is high, value tends to outperform growth. The R^2 for Model 3 is over 18%. These results are in further contrast with Model 4, in which the explanatory variable is *MKT* and its coefficient is statistically insignificant. Mechanically, this is surprising, as the correlation between *FIRM* and *MKT* is about 62%. Theoretically, however, this finding is in line with our expectations. *MKT* is not a cost on arbitragers, while *FIRM* is. The value–growth spread is greater when the cost to arbitraging away the anomaly is high. Model 5 includes all variables (except *MKT*, which is excluded due to its high correlation with *FIRM* potentially inducing multicollinearity problems). Again, *FIRM* is the only significant explanatory variable.

The coefficient on *FIRM* is economically as well as statistically significant. We see in the descriptive statistics that the mean of *F3_RVMG* is very close to zero (its mean indicates that by this measure, value has outperformed growth by 0.10% on average over a three-year period). However, we can see from Model 5 that a one standard deviation increase in *FIRM* (0.058) implies an increase in *F3_RVMG* of ($1.316 * 0.058 =$) 0.076. This implies a continuously compounded spread of about 250 basis points per year, for three years. By this measure, value outperforms growth, but only when the idiosyncratic volatility environment is a noisy one, costly for arbitragers.

Table 3 provides the same set of regressions, but the dependent variable is now the three-year

Table 3 Explaining the Value–Growth Spread.

	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	0.098	0.115	0.010	0.097	0.080
	(0.442)	(0.062)	(0.811)	(0.009)	(0.444)
CAPE	−0.000				−0.003
	(0.948)				(0.458)
YIELD_SLOPE		−0.019			−0.009
		(0.483)			(0.708)
FIRM			0.987**		1.141**
			(0.033)		(0.048)
MKT				−0.263	
				(0.380)	
Observations	444	444	444	444	444
R-Squared	0.000	0.016	0.106	0.007	0.133

The dependent variable in each regression is the three-year ahead value–growth spread, measured as the accumulated difference of the Fama–French HML factor.
Note: Parenthetical values are Newey–West adjusted *p*-values with using a 36-month bandwidth.

forward-looking spread *F3_HML*, instead of the Russell index spread. This is the value–growth spread most frequently studied by academics. Despite the different dependent variable definitions, the results in Tables 2 and 3 are quite similar. Again, neither *CAPE* nor *YIELD_SLOPE* are important determinants of the forward value–growth spread, while *FIRM* is positive and statistically significant. *MKT* again exhibits an insignificant association with the forward-looking value-spread variable. In Model 5, we find that *FIRM* is the sole significant explanatory variable of *F3_HML* in our time series regression. Using the parameters from Model 3, notice the drop-off in value outperformance in a low idiosyncratic volatility environment. When *FIRM* is equal to its mean (0.078), the expected value of *F3_HML* is 0.087, indicating a value outperformance of about 289 basis points per year. But when *FIRM* is one standard deviation (0.058) below its mean, the expected value outperformance is only about 99 basis points per year. The effect is still present, but dramatically reduced.

Tables 4 and 5 provide a similar set of regressions for *F2_RVMG* and *F2_HML*. The results are broadly similar to the results using the three-year forward-looking variables. Only the *FIRM* variable exhibits a statistically significant relationship with either dependent variable, and in both tables it is economically significant as well. Turning our attention to Model 5 in each table, it is noteworthy that the parameter estimates for the coefficients on *FIRM* are so similar to their Table 2 and 3 counterparts. Given the way the forward-looking return spread variables are defined via the summations in Equation (1), if the forward return increases associated with higher *FIRM* values were spread evenly throughout the forward-looking period, we would expect the coefficients in Tables 4 and 5 to be about 2/3 the values we see in Tables 2 and 3. They are not. When the forward-looking spread variable is derived from the Russell indices (in Tables 2 and 4), we see a change on the *FIRM* coefficient from 1.31 to 1.17, a decline about 11%. In Tables 3 and 5, when the dependent variables are derived from the Fama–French HML,

Table 4 Explaining the Value–Growth Spread.

	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	−0.030	−0.018	−0.082**	−0.004	−0.088
	(0.740)	(0.694)	(0.019)	(0.878)	(0.201)
CAPE	0.001				−0.002
	(0.789)				(0.638)
YIELD_SLOPE		0.012			0.022
		(0.539)			(0.197)
FIRM			1.009**		1.167**
			(0.031)		(0.024)
MKT				0.058	
				(0.814)	
Observations	460	460	460	460	460
R-Squared	0.006	0.001	0.158	0.000	0.193

The dependent variable in each regression is the two-year ahead value–growth spread, measured as the accumulated difference between the return to a long–short Russell Value—Russell Growth portfolio.

Note: Parenthetical values are Newey–West adjusted *p*-values with using a 24-month bandwidth.

Table 5 Explaining the Value–Growth Spread.

	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	0.062	0.054	−0.022	0.059*	0.015
	(0.541)	(0.299)	(0.544)	(0.039)	(0.858)
CAPE	−0.000				−0.003
	(0.962)				(0.376)
YIELD_SLOPE		0.002			0.013
		(0.931)			(0.568)
FIRM			0.993**		1.212**
			(0.021)		(0.023)
MKT				−0.080	
				(0.732)	
Observations	456	456	456	456	456
R-Squared	0.000	0.000	0.119	0.001	0.149

The dependent variable in each regression is the two-year ahead value–growth spread, measured as the accumulated difference of the Fama–French HML factor.
Note: Parenthetical values are Newey–West adjusted *p*-values with using a 24-month bandwidth.

we actually see an increase in the estimate of the coefficient, from 1.14 to 1.21. We can interpret the relative stability in these coefficients as an indication that the third year of the forward-looking return is comparatively less important in reaping the benefits of the *FIRM*-related value outperformance relative to growth.

In Tables 6 and 7, we see that the shorter forward-looking time horizon does begin to have the

Table 6 Explaining the Value–Growth Spread.

	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	−0.007	−0.018	−0.048**		−0.048
	(0.896)	(0.498)	(0.049)		(0.303)
CAPE	0.000			−0.004	−0.001
	(0.956)			(0.738)	(0.496)
YIELD_SLOPE		0.011			0.017
		(0.374)			(0.115)
FIRM			0.567		0.689*
			(0.120)		(0.061)
MKT				0.035	
				(0.828)	
Observations	472	472	472	472	472
R-Squared	0.000	0.015	0.099	0.000	0.141

The dependent variable in each regression is the one-year ahead value–growth spread, measured as the accumulated difference between the return to a long–short Russell Value—Russell Growth portfolio.
Note: Parenthetical values are Newey–West adjusted *p*-values with using a 12-month bandwidth.

Table 7 Explaining the Value–Growth Spread.

	Model 1	Model 2	Model 3	Model 4	Model 5
Constant	0.034	0.017	−0.024	0.025	−0.003
	(0.583)	(0.062)	(0.357)	(0.130)	(0.954)
CAPE	−0.001				−0.002
	(0.894)				(0.338)
YIELD_SLOPE		0.006			0.012
		(0.733)			(0.421)
FIRM			0.620*		0.769**
			(0.068)		(0.035)
MKT				0.017	
				(0.910)	
Observations	468	468	468	468	468
R-Squared	0.001	0.003	0.086	0.000	0.118

The dependent variable in each regression is the one-year ahead value–growth spread, measured as the accumulated difference of the Fama–French HML factor.
Note: Parenthetical values are Newey–West adjusted *p*-values with using a 12-month bandwidth.

expected deleterious effect on the coefficients. Again concentrating on Model 5, the *FIRM* coefficient is significant (at the 10% level) in Table 6 when *F1_RVMG* is the dependent variable. Its magnitude is about 60% the corresponding value that we see in Table 4. Similarly, in Table 7 when *F1_HML* is the dependent variable, the Model 5 coefficient on *FIRM* is still significant at the 5% level, and similarly declines to around 60% from the corresponding value in Table 5.

3 An Out-of-Sample Check—Looking Backward

The period of 1979 to the present is a natural lens to test the relationship between *FIRM* and the value–growth spread for several reasons—most notably, the introduction of practitioner-oriented indices with the proper coverage. Furthermore, transaction costs have dropped substantially over recent decades, to allow the kind of arbitrage trading that drives our result. Transaction cost differences can have notable effects through time. For example, Stoll and Whaley (1983) find that part of the small firm effect is driven by transaction costs.

While the Russell 1000 Value and Growth indices do not have historical values prior to 1979, Fama and French's HML factor is available back to 1926. The transaction costs of this earlier period are considerably higher than in the modern era, and so it is not clear whether the relationship will hold in such a way as to be comparable with our findings in Section 3. However, we can extend the observations back prior to 1979 to get a sense of the robustness of the result. Interestingly, Jones (2002) provides an extensive study on the historical evolution of transaction costs in U.S. public stock markets and finds that prior to 1968, NYSE transaction costs are linear—trading 1,000 shares is 10 times as costly as trading 100 shares. This began to change in 1968, and did so gradually until 1975, when commissions were fully deregulated. While bid–ask spread data are not completely available for this period, such spreads are generally larger, the farther back in time we look.

We therefore extend our sample back to 1968, using this time as our break point between transaction costs so onerous that value–growth arbitrage is not possible, and the modern era in which the transaction costs have dropped so far as to make the holding cost of idiosyncratic volatility the primary cost hurdle to arbitrage. Of course, this dividing line is somewhat arbitrary, and no such strict dividing line truly exists. But perhaps the slightly lower transaction costs and bid–ask spreads of the 1968–1979 time period relative to the pre-1968 environment, while higher than our primary 1979–2018 time period, still provide an environment with which we may test the robustness of our result.

In Table 8, we present the parameter estimates for the regression equation in Equation (7), including observations since 1968. The dependent variable is *F3_HML*. We exclude any control variables, since none were statistically significant when we examined them in Section 3. Model 1 is provided for reference and shows the parameter estimation using the time period of February 1979 through December 2018. Model 2 shows the parameter estimates for the older time period only, January 1968 through January 1979. The models are quite consistent. The coefficient on *FIRM* is positive, and is almost 170% larger than in the latter period. The parameter is significant at the 10% level (its reduced significance primarily driven by the much smaller number of observations). Model 3 provides the parameter estimates using the entire sample period.

The results in Table 8 raise the question of why the parameter estimate is so much greater in the early time period. It may be that the transaction costs of the earlier period, while quite high, are still low enough to allow the possibility of arbitrage under ideal circumstances. However, these ideal circumstances require lower idiosyncratic volatility than in the later period, implying that as idiosyncratic volatility levels increase, arbitrage rapidly becomes less plausible and behavioral forces rule the day. Rigorous testing of this conjecture is beyond the scope of this paper. Consistent with this hypothesis, but by no means proof of it, the relationship between *F3_HML* and *FIRM* is highly inconsistent prior to 1962, when transaction costs were notably higher.

We can see the consistency of the relationship between the two time periods through the scatterplots illustrated in Figure 1. Panel A demonstrates the relationship for the 444 observations of our primary sample period. The positive relationship between *F3_HML* and *FIRM* is quite evident. In particular, when idiosyncratic volatility is high, forward spread returns of value over growth are typically quite high. There are four interesting

Table 8 The Value–Growth Spread Through Time.

	Model 1 (1979–2018)	Model 2 (1968–1978)	Model 3 (1968–2018)
Constant	0.010	0.009	0.010
	(0.811)	(0.947)	(0.811)
FIRM	0.987**	2.646*	0.935**
	(0.033)	(0.073)	(0.010)
Observations	444	133	577
R-Squared	0.106	0.105	0.074

The dependent variable in each regression is the three-year ahead value–growth spread, measured as the accumulated difference of the Fama–French HML factor.
Note: Parenthetical values are Newey–West adjusted *p*-values with using a 36-month bandwidth.

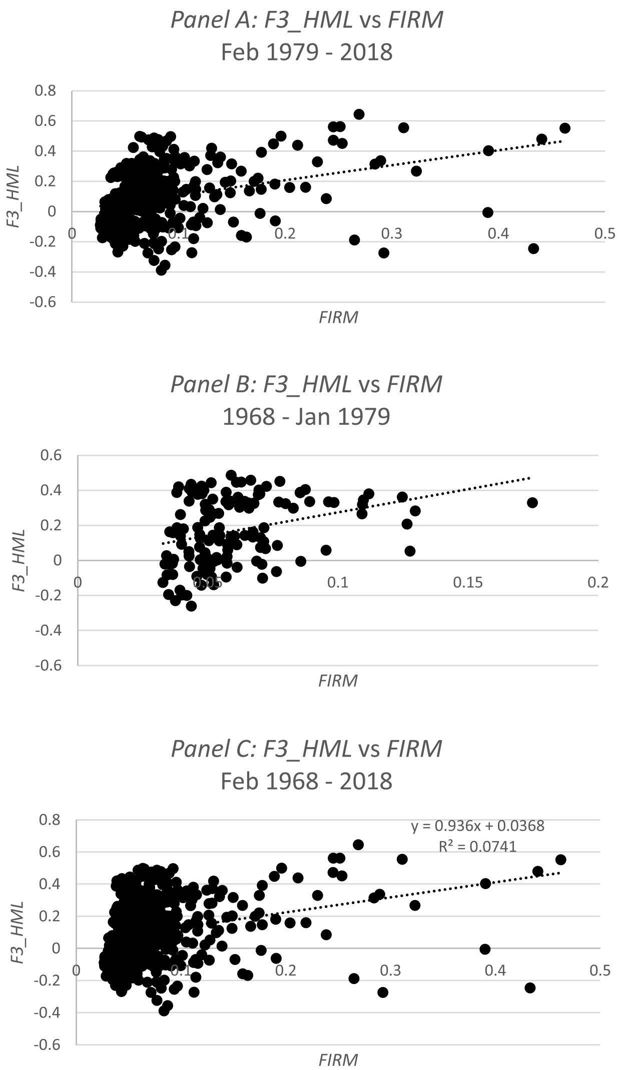

Figure 1 Value–Growth Spread Variable Through Time.

outliers located in the lower right quadrant of the panel. These four observations, all of which have *FIRM* values greater than 0.25 (about three standard deviations above the mean) and negative forward-looking returns, are clustered in two time periods that exhibit idiosyncratic volatility spikes—the October 1987 crash, and Fall of 2008. It is puzzling as to why these events present as such outliers to our results, but it is worth observing that they are associated with relatively transitory spikes in idiosyncratic volatility. It may be that traders become sequentially aware of arbitrage opportunities in the vein of Abreu and Brunnermeir (2002), and the transitory nature of these spikes causes the opportunity to pass before arbitragers can capitalize on the mispricing. The older period presented in Panel B does not have idiosyncratic volatility spikes of this magnitude, and correspondingly does not exhibit any such outliers. In Panel C we combine the observations to observe that the pattern is remarkably consistent over five decades.

4 Conclusion

The excess returns to value stocks relative to growth stocks over long-time horizons is well established in the literature. However, little evidence has been found in support of the *predictability* of this relationship. It may well be that the predictability of this relationship is predicated upon the existence of a sufficiently high idiosyncratic risk environment to prevent arbitragers from capitalizing on price discrepancies. Such would be the case if the origin of the value–growth spread were behavioral in nature.

By demonstrating that there is a positive relationship between the idiosyncratic volatility environment and future value–growth returns, we suggest that the origin of the value–growth spread may indeed be behavioral. This suggestion then points to an additional dimension for portfolio managers to consider when deciding when to tilt a portfolio toward growth or value. While we find that neither CAPE nor the slope of the yield curve is important determinant of future value–growth spreads, we do find that high idiosyncratic volatility environments are strongly associated with positive future value–growth spreads. These spreads are statistically and economically significant even with relatively short holding periods. For example, we find that a one standard deviation increase in the idiosyncratic volatility environment is associated with a 7.6% continuously compounded increase in the accumulated spread between the Russell 1000 Value and Growth indices over a three-year horizon. This relationship holds for these common practitioner indices, as well as the more academically oriented "high minus low" indices of Fama and French (1992).

Notes

[1] This argument is consistent with Abreu and Brunnermeir (2002) who find that delayed arbitrage is a consequence of arbitragers becoming sequentially aware of mispriced assets.

[2] See "Construction and Methodology—Russell U.S. Equity Indexes" the most recent of which may be found at https://www.ftserussell.com/products/indices/russell-us-style for further information. Our reference was the May 2019 iteration of this document.

[3] We define industries by mapping SIC codes to the 49 industry categories described in Fama and French (1997).

[4] For the construction of the CAPE measure, and a discussion of its possible shortcomings and/or modification, see Siegel (2016).

[5] This can be found at http://www.econ.yale.edu/~shiller/data.htm.

[6] This approach is quite similar to Harvey (1989).

[7] It is worth noting that this approach is theoretically appropriate, but quite conservative. For example, if we empirically examine the *F3_HML* series without knowledge of its construction (using a Box–Jenkins methodology), we find the autocorrelations become statistically insignificant after 17 lags rather than 36.

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