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Residual Income Valuation and Stock Returns: Evidence From a Value-to-Price Investment Strategy*

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ABSTRACT

This paper contributes to the accounting and asset pricing anomalies literature by investigating the performance of value-to-price (V/P) strategies, and the relationship between V/P ratio and various risk proxies. If the V/P ratio successfully predicts future returns at stock level, we hypothesize that portfolios based on the V/P ratio generate excess returns and consist of companies that are undervalued for extended periods. Both overlapping and non-overlapping returns are used to test the risk/mispricing explanation of the V/P strategy. Results for the US market show that high V/P portfolios outperform low V/P portfolios across horizons extending from 1 to 3 years. The V/P ratio is positively correlated to future stock returns after controlling for firm characteristics, which are well-known risk proxies. Findings also indicate that profitability and investment add explanatory power to the Fama–French three-factor model and for stocks with V/P ratio close to 1. However, these factors cannot explain all variation in excess returns especially for Years 2 and 3 and for stocks with high V/P ratios. Finally, portfolios with the highest V/P stocks select companies that are significantly mispriced relative to their equity (investment) and profitability growth persistence in the future.

JEL Classification: G11, G12, G14

1 | Introduction

Over the last three decades, researchers have investigated the puzzling features of value-to-price (V/P) investment strategies. This strategy is more successful and leads to higher abnormal returns, over longer horizons, than simple market multiples do (Ali et al. 2003a; Frankel and Lee 1998; Hwang and Lee 2013; Goncalves and Leonard 2023; Cong et al. 2023).[1] The V/P strategy originates from the work of Frankel and Lee (1998), who employ the residual income valuation model to estimate firms' intrinsic values and demonstrate that the resulting abnormal returns cannot be explained by differences in market betas, firm size, or book-to-market (B/M) ratios. Ali et al. (2003a) show that V/P anomalies are concentrated around earnings announcement dates.[2] Moreover, Hwang and Lee (2013) find that the Fama–French three-factor model cannot fully explain V/P strategy's excess returns, with the V/P factor accounting for only a portion of the observed premium.[3] Collective evidence supports the mispricing explanation of the V/P anomaly. Prior research has mainly focused on first-year returns, paying limited attention to second- and third-year portfolio performance. If the V/P ratio successfully predicts future returns at the stock level, we hypothesize that portfolios sorted on the V/P ratio generate significant excess returns, and consist of companies that are undervalued over investment periods that extend up to 3 years.[4] If excess returns persist at the portfolio level, this pattern is difficult

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to reconcile with standard risk-based models and instead suggests either limits to arbitrage or exposure to non-standard systematic risks (e.g., share characteristics, clustering within industries).[5] V/P portfolios are formed, and factor models are employed to assess the magnitude of abnormal returns over both short- and long-term investment horizons (Hou et al. 2015; Fama and French 2015).[6] This study contributes to the finance literature in several important ways. First, fundamental stock values are calculated using the residual income model (RIM) of Ohlson (1995), which integrates historical accounting information with 1-year-ahead analysts' earnings forecasts (see also Feltham and Ohlson 1995; Barth et al. 1999; Dechow et al. 1999; Myers 1999). The valuation model employed here differs from those in prior studies as it allows for accounting conservatism (or book values) to affect net income, and equity prices to be estimated from a structured system of equations.[7] Second, the study offers new empirical evidence for the mispricing versus risk explanation of the V/P anomaly at both the stock and portfolio levels. In particular, the relationship between the V/P ratio, firm characteristics commonly interpreted as risk proxies and long-horizon stock returns is examined.[8] Finally, the paper evaluates the extent to which standard asset pricing factor models can account for the puzzling return patterns associated with V/P-sorted portfolios, thereby assessing whether any observed premium reflects compensation for systematic risk or persistent mispricing.[9]

The dataset is constructed by merging COMPUSTAT, CRSP, I/B/E/S for all non-financial firms listed in AMEX, NYSE, and NASDAQ over the period 1987–2015. V/P quintile portfolios are formed, with Portfolio 1 comprising firms with the lowest V/P ratio and Portfolio 5 comprising firms with the highest V/P ratio. Portfolio returns in Years 1, 2, and 3 are examined using standard asset pricing factor models. Overlapping portfolio returns are also estimated, in which, at any given month t, the V/P strategy simultaneously holds portfolios selected in the current year (t), the previous year (t–1), and 2 years prior (t–2). Finally, since selected stocks are held for 3 years, additional results are generated using dividend-adjusted monthly excess returns.

The findings reveal that high V/P portfolios consistently outperform low V/P portfolios across horizons extending from 1 to 3 years, with performance differentials becoming more pronounced at longer horizons. Moreover, stocks in the highest V/P quintile exhibit higher B/M ratios, smaller firm size, and slightly greater beta exposure than those in the lowest V/P quintile; consistent with prior empirical evidence (Frankel and Lee 1998; Ali et al. 2003a; Goncalves and Leonard 2023; Cong et al. 2023). At the firm level, panel data regressions, fixed effect treated by year and industry, are used to examine the relationship between long horizon (buy-and-hold) returns and various risk characteristics, including the V/P ratio. High V/P stocks are characterized by greater idiosyncratic volatility, higher return-on-asset (ROA) volatility, smaller size, and lower beta. Importantly, the relationship between long-run stock returns and the V/P ratio is positive and statistically significant, while the effect of firm size (idiosyncratic volatility) and beta (earnings variability) on returns is negative (positive) and statistically significant. These results align with prior evidence showing that the value effect is stronger among stocks with higher idiosyncratic volatility, smaller size, and lower beta risk (Shleifer and Vishny 1997; Ali et al. 2003b; Frazzini and Pedersen 2014).

Further evidence from asset pricing factor models demonstrates that V/P excess returns vary with differences in market betas, firm size, B/M ratios, operating profitability and investment across quintile portfolios, consistent with the findings of Hou et al. (2015) and Fama and French (2015). Notably, the loadings on the risk factors do not increase monotonically across portfolios sorted from low to high V/P ratios, while the profitability and investment factors exhibit significant loadings primarily in the intermediate V/P portfolios. Moreover, asset pricing factors do not fully account for the observed variation in excess returns, particularly among high V/P portfolios and during the second and third years following portfolio formation. Specifically, portfolios with the highest V/P ratios appear to select firms that are significantly mispriced relative to the persistence of their expected investment and profitability growth. In essence, the V/P ratio captures information about the timing and persistence of future fundamentals that is not immediately incorporated into prices. Adding to this argument, the strong second- and third-year performance of the highest V/P portfolio largely explains the difference between first-year and overlapping returns.

The next section of this paper reviews the literature review on the V/P anomaly and the competing mispricing versus risk explanations of it. Sections three and four describe the methodological framework and the data used for the empirical analysis, respectively. Section five presents and discusses the main empirical results. The final section concludes the paper and offers suggestions for future research.

2 | Related Literature

2.1 | Value-to-Price and Stock Returns

Value strategies focus on buying stocks with low market prices relative to fundamentals such as earnings, dividends, and book values (Lakonishok et al. 1994; Asness et al. 2013; Novy-Marx 2013). Lakonishok et al. (1994) find that value stocks yield an extra 10% return on average over glamour stocks, which they attribute largely to underpricing relative to their risk and return characteristics rather than to higher fundamental risk.[10] Novy-Marx (2013) shows that only highly profitable value stocks generate significant excess returns, while Asness et al. (2013) document consistent value return premia across eight diverse market and asset classes.[11] Goncalves and Leonard (2023) find that the premium associated with the fundamental-to-market (F/M) ratio subsumes the B/M ratio premium and has remained relatively stable over time, whereas the cross-sectional correlation between F/M and B/M decreased over time, inducing an apparent decline in the value premium. Also, Cong et al. (2023) document that V/P, the ratio of Residual-Income-Model (RIM) based valuation to market price, subsumes the power of B/M ratio and generates significant returns after adjusting for common factors. Lazzati and Menichini (2018) show that a simple portfolio strategy based on the difference between market and estimated values earns considerably positive returns that cannot be explained the Fama–French three- or five-factor models.

One explanation of this slow price convergence is the speed at which long-term fundamental information is incorporated in stock prices. Frankel and Lee (1998) use a version of the RIM that incorporates financial analysts' forecasts to estimate the fundamental value and show that the V/P ratio reliably predicts cross-sectional stock returns, particularly over longer horizons.[12] Dechow et al. (1999) provide evidence that high V/P decile portfolios produce better 12-month returns compared to low V/P portfolios.[13] The superior explanatory power of the simple RIM may reflect investors' tendency to overweight information contained in analysts' earnings forecasts while underweighting information embedded in current earnings and book value. Lee and Swaminathan (1999) and Lee et al. (1999) investigate the relationship between stock returns and intrinsic value and show that an (aggregate) V/P ratio has statistically reliable predictive power, not only for individual stock returns but also for returns on a stock index and a small-stock portfolio. Their work also highlights that using a time-varying discount rate and a 1-year analysts' forecast are crucial for the success of the V/P strategy.[14] On the contrary, Xu (2007) concludes that the V/P ratio has no incremental power in explaining abnormal returns beyond its components (book value, earnings, and analysts' forecasts), particularly the analysts' earnings forecasts, while the reason for the V/P effect is investors' subjective expectations regarding its underlying variables. Likewise, Myers (1999) and Lo and Lys (2000) raise concerns about Frankel and Lee's implementation of the residual income valuation model.[15] An alternative explanation of the V/P effect is that it reflects cross-sectional risk differences.

2.2 | Value-to-Price, Mispricing, and Risk

Academics and practitioners agree that the V/P ratio predicts the cross-section of stock returns for up to 3 years. However, the underlying reasons for this strong predictive power remain an open question. Frankel and Lee (1998) present evidence that the V/P anomaly reflects temporary market mispricing, while not entirely ruling out the possibility that V/P-based strategies are risky along other dimensions. Ali et al. (2003a) investigate the mispricing versus risk explanations of the V/P anomaly and show that the anomaly is largely concentrated around earnings announcement dates, supporting the mispricing explanation.[16] Ali et al. (2003b) find that the value (B/M) effect is greater for stocks with higher idiosyncratic volatility. They also find that when arbitrage is costly and investor sophistication is low, the value effect is high, providing further support for the mispricing explanation. Shleifer and Vishny (1997) argue that strategies designed to exploit mispriced assets are both risky and costly, which limits arbitrage activities, thereby allowing mispricing to persist over long periods. Wei and Zhang (2007) show that the profitability of the V/P strategy is concentrated in stocks with low arbitrage risk, whereas it is extremely weak in stocks with extremely high arbitrage risk, further supporting the mispricing explanation of V/P anomaly.[17] Additionally, Piotroski and So (2012) demonstrate that returns to value/glamour investment strategies are strongest among firms where expectations implied by current prices are dissimilar with the strength of their fundamentals. Golubov and Konstantinidi (2019) examine the value premium using the multiples-based market-to-book decomposition and find that the market-to-value component drives the entirety of value strategy returns, while the value-to-book component exhibits no return predictability in either portfolio sorts or firm-level regressions.[18] Unlike previous studies that focus on the general predictive ability of the V/P strategy, Johnson and Xie (2004) investigate the movement of stocks in the extreme V/P quantile portfolios.[19] They find that less than 30% of stocks in these extreme V/P quantiles exhibit price convergence to fundamental values after 36 months and that the abnormal returns of the V/P strategy are primarily driven by this small subsample of stocks.

Although existing evidence supports the mispricing explanation of V/P strategies, none of them rules out completely the possibility that high V/P stocks may be riskier along certain dimensions than low V/P stocks (Frankel and Lee 1998; Myers 1999; Lo and Lys 2000; Kothari 2001; Beaver 2002; Ali et al. 2003a).[20] Inferences about long-term market mispricing are often complicated by omitted risk factors, the extended horizon over which the anomaly unfolds, and methodological concerns such as survivorship bias, statistical biases, and performance measurement issues. Hwang and Lee (2013) construct a V/P factor-mimicking portfolio and find that the VP factor dominates the V/P characteristic in explaining stock returns.[21] Hahn and Lee (2006) also provide evidence that the size and value premia compensate investors for greater exposure to risks related to changing credit market conditions (default spread) and interest rates (term spread), respectively.[22] Lettau and Ludvigson (2001) show that value stocks earn higher average returns than growth stocks because they are more highly correlated with consumption growth during economic downturns, when risk premia are high.[23]

2.3 | Research Question—Hypothesis

Asset pricing theory posits that cross-sectional variation in stock returns arises either as compensation for systematic risk or from persistent mispricing driven by limits to arbitrage. Traditional value measures, particularly the B/M ratio, have been extensively documented as capturing variation in expected returns; however, alternative valuation ratios may contain incremental information about firms' fundamental value relative to market prices (Lakonishok et al. 1994; Asness et al. 2013; Novy-Marx 2013). This study investigates the pricing relevance of the V/P ratio at both portfolio and firm levels. First, we assess whether V/P-sorted portfolios outperform traditional B/M-sorted portfolios, thereby evaluating the incremental information content of V/P relative to a well-established value metric (Table 1). The study then examines whether high V/P portfolios earn superior returns compared to low V/P portfolios and analyze the underlying characteristics in terms of firm size, market beta, and B/M ratios (Table 1). The V/P ratio, defined as the ratio of estimated intrinsic value to observed market price, is intended to more directly capture deviations from fundamental value (Ali et al. 2003a; Frankel and Lee 1998; Hwang and Lee 2013; Goncalves and Leonard 2023; Cong et al. 2023).[24]

At the firm level, we examine whether long-run stock returns are associated with the V/P ratio after controlling for conventional risk characteristics (Shleifer and Vishny 1997; Ali et al. 2003b; Campbell and Vuolteenaho 2004; Frazzini and Pedersen 2014). If V/P captures economically meaningful information about expected returns beyond observable firm characteristics, then stock returns should be significantly related to the V/P ratio (Table 4). To determine whether V/P contains information distinct from established valuation metrics, we further analyze

TABLE 1 | Performance and characteristics of quantile portfolios formed by ME, B/M, and V/P ratios.

Panel A – Market equity portfolios (in-sample size quintiles)							
	Q1 low ME	**Q2**	**Q3**	**Q4**	**Q5 high ME**	**All firms**	**Q5–Q1 diff.**
ME	274	1014	2392	5837	20,491	6984	20,216***
V/P	2.243	1.285	1.081	0.992	0.904	1.476	−1.339***
B/M	1.670	1.110	0.859	0.692	0.470	1.104	−1.201***
Beta	1.262	1.291	1.209	1.164	1.003	1.186	−0.259***
Ret12	0.187	0.140	0.151	0.130	0.109	0.152	−0.078***
Ret24	0.411	0.329	0.324	0.298	0.247	0.340	−0.168***
Ret36	0.585	0.426	0.366	0.388	0.304	0.447	−0.286***
SRet12	0.069	0.027	0.028	0.005	0.005	0.035	−0.063***
SRet24	0.124	0.062	0.043	0.019	0.017	0.067	−0.106***
SRet36	0.179	0.097	0.028	0.037	0.027	0.094	−0.151***
Obs.	3325	3314	3315	3296	3330	16,580	
Panel B – Book to market (B/M) portfolios							
	Q1 low B/M	**Q2**	**Q3**	**Q4**	**Q5 high B/M**	**All firms**	**Q5–Q1 diff.**
B/M	0.155	0.320	0.478	0.702	2.496	1.104	2.340***
V/P	0.890	1.097	1.343	1.678	2.370	1.476	1.480***
ME	10,846	7784	6062	5546	4686	6984	−6160***
Beta	1.219	1.168	1.154	1.117	1.241	1.186	0.022
Ret12	0.136	0.141	0.153	0.152	0.177	0.152	0.041**
Ret24	0.300	0.314	0.340	0.334	0.411	0.340	0.111*
Ret36	0.386	0.405	0.450	0.453	0.542	0.447	0.156**
SRet12	0.024	0.027	0.037	0.033	0.054	0.035	0.030**
SRet24	0.042	0.048	0.069	0.058	0.118	0.067	0.076*
SRet36	0.058	0.066	0.083	0.101	0.165	0.094	0.106*
Obs.	3325	3314	3315	3296	3330	16,580	
Panel C – Value-to-price (V/P) portfolios							
	Q1 low V/P	**Q2**	**Q3**	**Q4**	**Q5 high V/P**	**All firms**	**Q5–Q1 diff.**
V/P	0.580	0.876	1.142	1.531	3.184	1.476	2.604***
B/M	0.538	0.647	0.858	1.368	1.800	1.104	1.261***
ME	12,400	7747	5033	3086	944	6984	−11,455**
Beta	1.10	1.04	1.03	1.13	1.28	1.186	0.18
Ret12	0.148	0.149	0.137	0.176	0.201	0.152	0.053*
Ret24	0.330	0.307	0.325	0.365	0.467	0.340	0.137**
Ret36	0.413	0.382	0.383	0.449	0.691	0.447	0.278**
SRet12	0.028	0.024	0.014	0.048	0.060	0.035	0.032*
SRet24	0.050	0.035	0.042	0.070	0.138	0.067	0.088*
SRet36	0.077	0.043	0.046	0.083	0.223	0.094	0.145*
Obs.	3325	3314	3315	3296	3330	16,580	

Note: All the NYSE, AMEX, and NASDAQ stocks in the sample are sorted into five quintile portfolios based on ME, B/M, or V/P at the end of June each year. ME is the market value of equity at the end of June of year t. V/P is the fundamental value of year $t-1$, measured using the previous 5 years' data, divided by the stock price at the end of June of year t. B/M is the book value of equity at the end of December of year $t-1$ divided by the market value of equity at the end of June of year t. The stocks in Q1 (Q5) are the stocks with the lowest (highest) ME, B/M, or V/P. Each panel of the table reports the characteristics of the quintile portfolios. Beta is the average post-ranking market betas estimated using monthly returns over the next 36 months. Ret12, Ret24, and Ret36 are the average

(Continues)

TABLE 1 | (Continued)

buy-and-hold returns over 12, 24, and 36 months, respectively, beginning from July of Year t. SRet12, SRet24, and SRet36 are size-adjusted returns over 12, 24, and 36 months, respectively, beginning from July of Year t. The size-adjusted returns are calculated as the difference between the raw returns and the corresponding size index returns where the cutoff point of the size deciles is based on all stocks. Obs. denotes the number of observations in each quintile portfolio and it applies to all variables except returns. Q5–Q1 diff. represents the differences between the top portfolio and bottom portfolio. The statistical significance of the difference is based on t statistics derived from the annual mean and the standard error of the variables. The procedures of Newey and West (1987) were followed to adjust for the serial correlation for Ret24, Ret36, SRet24, and SRet36 due to overlapping holding periods.
*, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively (two-sided tests).

its association with B/M ratios and other firm-level risk characteristics (Table 3). At the portfolio level, we further evaluate whether V/P-sorted portfolios generate statistically significant abnormal returns after accounting for standard asset pricing models, including the CAPM, Fama–French three-factor, and five-factor models (Hou et al. 2015; Fama and French 2015). If V/P proxies for unobserved risk exposures, portfolios with high V/P ratios should earn higher expected returns that are fully explained by standard factor models (Piotroski and So 2012; Wei and Zhang 2007). Alternatively, if high V/P ratios capture mispricing arising from investor underreaction, behavioral biases, or constraints on arbitrage, abnormal returns may persist even after controlling for common risk factors and over extended horizons (Golubov and Konstantinidi 2019; Jaffe et al. 2019).

Finally, we analyze the multi-year persistence of V/P portfolio returns. If high V/P ratios reflect mispricing rather than risk compensation, return predictability should extend beyond the first year following portfolio formation, particularly into the second and third years, consistent with gradual price adjustment and limited arbitrage (Tables 5 and 7). Performance is measured using overlapping portfolios over a 3-year postformation horizon, with particular emphasis given on the persistence of abnormal returns in Years 2 and 3 (Tables 6and 8). This intertemporal analysis provides insight into whether V/P-based mispricing is corrected gradually, or alternatively, whether the V/P ratio captures information about the timing and persistence of future fundamentals that is not immediately incorporated into prices.

3 | Methodology and Empirical Implementation

This section describes the empirical implementation of the RIM, while its theoretical foundations are summarized in the Appendix. It then presents the regression specifications used to examine the relationship between the V/P ratio, long-horizon returns, and firm-level risk characteristics. Finally, we outline the asset pricing factor models employed to evaluate the performance of V/P trading strategies.

3.1 | Empirical Implementation of the Residual Income Valuation Model

This study adopts the residual income valuation model as developed by Feltham and Ohlson (1995) and Ohlson (1995) and implemented by Dechow et al. (1999), Barth et al. (1999), Barth et al. (2005), and Myers (1999).[25] The model in Equation (1) consists of three forecasting Equations (a, b, and c) and one valuation Equation (d).[26] The valuation and forecasting parameters are estimated simultaneously within a system of equations to satisfy no-arbitrage conditions, maintain clean surplus relations, and ensure the internal consistency of the model. In other words, the simultaneous estimation of the model ensured one-to-one mapping between the forecasting equations and the valuation equation (Barth et al. 2005; Pope and Wang 2005; Myers 1999; Tsay et al. 2008; Tsay et al. 2009; Wang 2013). Furthermore, due to the possible correlation among the error terms ($\varepsilon_{1,it}$, $\varepsilon_{2,it}$, $\varepsilon_{3,it}$, and u_{it}) in Equations (a–d), seemingly unrelated regression (SUR) is employed to estimate the system of equations (Zellner 1962; Gallant 1975; McElroy and Burmeister 1988).[27]

Following Barth et al. (2005) and Wang (2013), the predicted market value for each firm-year is estimated using data from the past 5 years for all firms in the industry, excluding any firm-specific data for the target firm being predicted.[28] Thus, the prediction was strictly considered to be out of sample prediction. In other words, the parameters and errors in forecasting and valuation equation are estimated using a jackknife procedure. For instance, to estimate the parameters for Firm i in Industry j for the Year t, the data for all firms in Industry j for the period from Year t–4 to Year t were included except the data for Firm i in Year t. Also, the parameters were firm-year-industry specific because they incorporate data updated on a yearly basis. Parameters can vary across industries as a result of differences in economic environment and accounting practices, while the level of conservatism and cost of capital associated with abnormal earnings is also allowed to change by industry. Finally, the V/P ratio is defined as the fundamental value V, proxied by MV_{it} in Equation (1d), of Year t–1, divided by the stock price at the end of June of Year t.[29] We use a firm's equity at the end of June of Year t to compute its B/M, V/P ratios, and to measure its size.

For the purposes of this paper, different discount rates (r) are used to calculate abnormal income (NI_{it}^{a}). First, a range of discount rates from 8% to 16% is used. Second, CAPM and Fama and French's three-factor model is employed to calculate the discount rate on a 5-year rolling basis (Fama and French 1997). Empirical results did not change significantly between different methods. To maintain simplicity and be consistent with other studies (Barth et al. 2005; Tsay et al. 2008), a 12% discount rate is used.

$$NI_{it}^{a} = \omega_{10} + \omega_{11} NI_{it-1}^{a} + \omega_{12} BV_{it-1} + \omega_{13} \nu_{it-1} + \varepsilon_{1,it} \tag{1a}$$

$$BV_{it} = \omega_{22}\, BV_{it-1} + \varepsilon_{2,it} \tag{1b}$$

$$\nu_{it} = \omega_{33}\, \nu_{it-1} + \varepsilon_{3,it} \tag{1c}$$

TABLE 2 | Pearson and Spearman correlation matrix among V/P and various risk characteristics.

	V/P	**Analysts**	**Ln(ME)**	***D/M***	**Beta**	**Ivolatility**	**Std ROA**	***Z* score**	***B/M***
V/P	–	−0.275***	−0.478***	0.161***	0.118***	0.437***	0.112***	−0.017	0.148***
Analysts	−0.391***	–	0.721***	−0.125***	−0.053***	−0.270***	−0.075***	−0.157***	−0.159***
Ln(ME)	−0.553***	0.754***	–	−0.139***	−0.103***	−0.491***	−0.115***	−0.173***	−0.165***
D/M	0.196***	0.039***	0.086***	–	0.034***	0.035***	−0.038***	−0.146***	0.791***
Beta	0.116***	−0.032***	−0.092***	−0.059***	–	0.2912***	0.136***	0.015*	0.021***
Ivolatility	0.361***	−0.327***	−0.538***	−0.178***	0.290***	–	0.148***	0.101***	−0.006
Std ROA	0.154***	−0.135***	−0.222***	−0.223***	0.286***	0.369***	–	0.011***	−0.035***
Z score	−0.039	−0.176***	−0.201***	−0.341***	0.027***	0.130***	0.079***	–	−0.103***
B/M	0.577***	−0.237***	−0.303***	0.431***	0.025***	0.037***	−0.069***	−0.218***	–

Note: The table reports the Pearson (Spearman) correlation matrix over (under) the diagonal. V/P is the fundamental value of Year $t-1$, measured using the previous 5 years' data, divided by the stock price at the end of June in Year t. Analysts is the number of financial analysts following the stock, which is included in I/B/E/S files in the month following the annual earnings announcements. Ln(ME) is the logarithm of the market value of equity at the end of June in Year t. D/M is the ratio of the long-term debt at the end of December of Year t–1 to the market value of equity as measured at the end of June in Year t. Beta is measured using the capital asset pricing model (CAPM) using monthly data over the maximum of 36 previous months ending in the December of year t–1. Ivolatility is calculated as the standard deviation of the residual from the CAPM model using daily returns data that end on the last trading day of Year t–1. Std ROA is the standard deviation of return on assets over the previous 5 years ending in the December of Year t–1. Z score is an Altman (1968) score calculated as Z= 1.2×(Working Capital/Total Assets) + 1.4×(Retained Earnings/Total Assets) + 3.3×(Ebit/Total Assets) + 0.6×(Market Value of Equity/Book Value of Total Liabilities) + 1.0×(Sales/Total Assets). B/M is calculated as the book value of equity of Year t–1 divided by the market value of equity at the end of June in Year t.

*, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively (two-sided tests).

TABLE 3 | Regression of value-to-price ratio on various risk characteristics.

$$V/P = \beta_0 + \beta_1\textbf{Beta} + \beta_2\textbf{Ivolatility} + \beta_3 D/M + \beta_4\textbf{Ln(ME)} + \beta_5\textbf{Analysts} + \beta_6\textbf{Altman's } Z + \beta_7\textbf{Std(ROA)} + \beta_8 B/M + \varepsilon$$
Equation (3)

	Model I		Model II	
	β	*t* statistics	β	*t* statistics
Intercept	3.312	40.60***	2.55	26.58***
Beta	0.144	8.72***	−0.046	−6.92***
Ivolatility			3.99	17.32***
D/M			0.041	2.30**
Ln(ME)	−0.329	−49.03***	−0.28	−29.55***
Analysts			0.018	11.23***
Altman's Z			−0.167	−9.95***
Std(ROA)			1.33	6.92***
B/M	0.027	6.51***	0.018	2.18**
Industry dummy	Yes		Yes	
Year dummy	Yes		Yes	
Adj. R^2	26.5%		33.17%	
Obs.	16,548		16,548	
Years	1993–2014		1992–2014	

Note: The table reports the pooled regression of Equation (3) with year and industry fixed effect. The industry classification is based on Fama and French (1997), as reported in Table 1. V/P is the fundamental value of Year $t-1$ divided by the stock price at the end of June in Year t. Analysts is the number of financial analysts following the stock. Ln(ME) is the logarithm of the market value of equity at the end of June in Year t. D/M is the ratio of the long-term debt at the end of December in Year t–1 to the market value of equity as measured at the end of June in Year t. Beta is measured using the capital asset pricing model (CAPM) using monthly data over the maximum of 36 previous months ending at the December of Year t–1. Ivolatility is calculated as the standard deviation of the residual from the CAPM model using daily returns data ending on the last trading day of Year t-1. Std(ROA) is the standard deviation of return on assets over the previous 5 years ending in the December of Year t–1. Z score is an Altman's Z score (1968). B/M is calculated as the book value of equity of Year t–1 divided by the market value of equity at the end of June of Year t. Adj. R^2 is the adjusted R^2.
*, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively (two-sided tests).

$$MV_{it} = \alpha_0 + BV_{it} + \alpha_1 NI_{it}^a + \alpha_2 BV_{it} + \alpha_3 \nu_{it} + u_{it} \tag{1d}$$

$$\alpha_0 = \frac{(1+r)}{r} * \frac{\omega_{10}}{(1+r-\omega_{11})}$$

$$\alpha_1 = \frac{\omega_{11}}{(1+r-\omega_{11})}$$

$$\alpha_2 = \frac{(1+r)*\omega_{12}}{(1+r-\omega_{11})(1+r-\omega_{22})}$$

$$\alpha_3 = \frac{(1+r)*\omega_{13}}{(1+r-\omega_{11})(1+r-\omega_{33})}$$

where BV_{it} is the book value of equity; MV_{it} is the market value of equity; r is the cost of capital; NI_{it}^a is the residual income ($= NI_{it} - r * BV_{it-1}$); ν_{it} is other information; ω_{11} is the residual income persistence parameter ($0 < \omega_{11} < 1$); ω_{12} is the conservatism parameter[30]; ω_{22} is the book value persistence or growth parameter[31]; ω_{33} is the persistence parameter of other information ($0 < \omega_{33} < 1$); $\varepsilon_{1,it}$, $\varepsilon_{2,it}$, $\varepsilon_{3,it}$, and u_{it} are error terms; and i and t subscripts refer to the firm and year, respectively.

Two alternative approaches to estimate other information variables (υ) are employed. First, the procedures of Dechow et al. (1999) and Ohlson (2001) are followed. In particular, the other information variable (υ) is calculated as follows,

$$\upsilon_t = E_t\left[NI_{t+1}^a\right] - \omega \cdot NI_t^a \tag{2a}$$

$$E_t\left[x_{t+1}^a\right] = f_t^a = f_t - r \cdot BV_t$$

$$\upsilon_t = f_t^a - \omega \cdot NI_t^a$$

where $E_t[NI_{t+1}^a]$ is the conditional expectation of abnormal income for the period t+1 based on all information available at period t; f_t is the consensus of analysts' forecasts of expected earnings for period t+1; and ω is the persistence parameter of abnormal income and is estimated by ignoring other information variable of Equation (1a). Second, the approach of Bryan and Tiras (2007) is adopted to calculate the other information variable (υ)

TABLE 4 | Regression of long-run stock returns on V/P and various risk characteristics.

Ret36 =
$\boldsymbol{\beta_0 + \beta_1 V/P + \beta_2 \text{Beta} + \beta_3 \text{Ivolatility} + \beta_4 D/M + \beta_5 \text{Ln(ME)} + \beta_6 \text{Analysts} + \beta_7 \text{Altman's } Z + \beta_8 \text{Std(ROA)} + \beta_9 B/M + \varepsilon}$
Equation (4)

	V/P only		**Model I**		**Model II**	
	β	***t* statistics**	**β**	***t* statistics**	**β**	***t* statistics**
Intercept	0.522	9.24***	0.852	12.62***	0.647	7.94***
V/P	0.054	10.23***	0.031	4.67***	0.013	1.9**
Beta			0.009	0.93	−0.030	−2.58***
Ivolatility					1.431	7.49***
D/M					0.036	4.79***
Ln(ME)			−0.428	−9.35***	−0.037	−5.06***
Analysts					0.003	2.51**
Altman's Z					0.045	3.54***
Std(ROA)					−0.163	−1.29
B/M			−0.003	−1.23	−0.014	−3.25***
Ind. dummy	Yes		Yes		Yes	
Year dummy	Yes		Yes		Yes	
Adj. R^2	21.88%		22.50%		23.39%	
Obs.	12,733		12,707		11,693	

Note: The table reports the pooled regression of Equation (3) with year and industry fixed effect. The industry classification is based on Fama and French (1997), as reported in Table 1. V/P is the fundamental value of Year $t-1$ divided by the stock price at the end of June in Year t. Analysts is the number of financial analysts following the stock. Ln(ME) is the logarithm of the market value of equity at the end of June in Year t. D/M is the ratio of the long-term debt at the end of December in Year t–1 to the market value of equity as measured at the end of June in Year t. Beta is measured using the capital asset pricing model (CAPM) using monthly data over the maximum of 36 previous months ending in December of Year t–1. Ivolatility is calculated as the standard deviation of the residual from the CAPM model using daily returns data ending on the last trading day of year-1. Std(ROA) is the standard deviation of return on assets over the previous five years ending in the December of Year t–1. Z score is an Altman's Z score (1968). B/M is calculated as the book value of equity of Year t–1 divided by the market value of equity at the end of June of Year t. Adj. R^2 is the adjusted R^2.
*, **, and *** denote statistical significance at 10%, 5%, and 1%, respectively (two-sided tests).

as expressed below.

$$f_{i,t} = \delta_0 + \delta_1 NI_{i,t} + \delta_2 BV_{i,t} + \upsilon_{i,t} \tag{2b}$$

where $f_{i,t}$ is the consensus of analysts' forecasts for next year's earnings by firm i; $NI_{i,t}$ and $BV_{i,t}$ are the net income and book value of Firm i in Year t, respectively; δ_0, δ_1, and δ_2 are regression parameters; and $\upsilon_{i,t}$ is the regression residual, which also proxies for other information in Equation (2b). Bryan and Tiras (2007) regress the consensus of financial analysts' forecasts directly on the fundamental variables (BV and NI). Thus, the accuracy of the model depends on the accuracy of the regression residual only.[32] Both approaches give comparable results; hence, the main analysis here depends only on Dechow et al. (1999).[33]

3.2 | Value-to-Price, Risk Proxies, and Stock Returns

The risk explanation for the superior predictability of the V/P strategy is explored by evaluating the relationship between the V/P ratio and commonly used risk proxies at firm level (Equation 3). These factors are primarily motivated by previous studies (Fama and French 1993; Gebhardt et al. 2001). Frankel and Lee (1998) investigate the extent to which firm size, B/M ratio and firm beta explain the predictive power of the V/P strategy. Similarly, Ali et al. (2003a) and Hwang and Lee (2013) control for firm characteristics, which had been suggested by Gebhardt et al. (2001) and Gode and Mohnram (2003) as risk proxies. The following equation is estimated using year and industry fixed effects[34]

$$V/P = \beta_0 + \beta_1 \text{Beta} + \beta_2 \text{Ivolatility} + \beta_3 D/M + \beta_4 \text{Ln(ME)} + \beta_5 \text{Analysts} + \beta_6 \text{Altman's } Z + \beta_7 \text{Std(ROA)} + \beta_8 B/M + \varepsilon \tag{3}$$

where V/P is the V/P ratio; Beta is a measure of systematic risk; Ivolatility is a measure of unsystematic or idiosyncratic risk; D/M is the long term debt-to-market value ratio (leverage); Ln(ME) is a measure of firm size; Analysts is a measure of the financial analysts' coverage of the firm; Altman's Z is a measure of financial distress; Std(ROA) is a measure of earnings variability; and B/M is a measure of the B/M ratio (see appendix for details on the risk proxies used here).

TABLE 5 | One-factor, three-factor, and five-factor models' regression for quintile portfolios formed on (V/P).

Panel A: One factor model										
	$(R_{it} - R_{ft}) = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \varepsilon_t$ **(1)**									
	First year returns					**Overlapping returns**				
	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
α	0.001	0.001	0.001	0.001	0.004*	0.002*	0.002	0.001	0.002	0.006***
	(1.14)	(1.16)	(0.66)	(1.01)	(1.88)	(1.89)	(1.62)	(1.33)	(1.51)	(2.81)
β	1.094***	1.095***	1.007***	1.126***	1.269***	1.093***	1.050***	0.968***	1.083***	1.174***
	(39.37)	(34.49)	(26.60)	(25.91)	(21.31)	(42.81)	(35.00)	(28.97)	(27.13)	(22.93)
Adj. R^2	0.851	0.812	0.719	0.709	0.622	0.869	0.816	0.753	0.727	0.656
	GRS F value: 4.55					GRS F value: 11.450*				

Panel B: Three-factor model										
	$(R_{it} - R_{ft}) = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i\mathrm{SMB}_t + h_i\mathrm{HML}_t + \varepsilon_t$ **(2)**									
	First year returns					**Overlapping returns**				
	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
α	0.001	0.000	0.000	0.000	0.003	0.001*	0.001	0.000	0.000	0.004***
	(1.24)	(0.54)	(0.32)	(0.15)	(1.53)	(1.81)	(0.98)	(0.45)	(0.75)	(2.78)
β	1.050***	1.088***	1.015***	1.097***	1.200***	1.057***	1.048***	0.969***	1.063***	1.116***
	(40.39)	(38.32)	(33.03)	(33.85)	(25.35)	(44.85)	(40.85)	(38.68)	(38.36)	(29.15)
s	0.244***	0.277***	0.327***	0.578***	0.831***	0.270***	0.272***	0.355***	0.537***	0.757***
	(6.76)	(7.03)	(7.68)	(12.86)	(12.65)	(8.27)	(7.64)	(10.22)	(13.96)	(14.25)
h	−0.078**	0.292***	0.494***	0.489***	0.446***	0.027	0.329***	0.462***	0.518***	0.449***
	(2.12)	(7.22)	(11.29)	(10.60)	(6.62)	(0.81)	(9.00)	(12.95)	(13.13)	(8.24)
Adj. R^2	0.875	0.858	0.825	0.847	0.774	0.894	0.873	0.869	0.876	0.818
	GRS F value: 5.49					GRS F value: 13.23*				

(Continues)

TABLE 5 | (Continued)

Panel C: Five-factor model										
	$(R_{it} - R_{ft}) = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i\text{SMB}_t + h_i\text{HML}_t + r_i\text{RMW}_t + c_i\text{CMA}_t + \varepsilon_t$ (3)									
	First year returns					**Overlapping returns**				
	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
α	0.001	0.000	−0.002**	−0.001	0.003	0.001	0.000	−0.001	0.000	0.004**
	(0.96)	(0.64)	(−2.03)	(−1.06)	(1.41)	(1.54)	(0.48)	(−1.63)	(0.49)	(2.34)
β	1.062***	1.159***	1.123***	1.181***	1.205***	1.067***	1.126***	1.074***	1.135***	1.141***
	(33.88)	(34.70)	(32.06)	(31.03)	(21.12)	(37.56)	(37.98)	(38.76)	(34.92)	(24.77)
s	0.249***	0.331***	0.425***	0.633***	0.810***	0.267***	0.348***	0.458***	0.600***	0.761***
	(6.13)	(7.62)	(9.33)	(12.80)	(10.92)	(7.23)	(9.02)	(12.71)	(14.21)	(12.69)
h	−0.106**	0.152***	0.295***	0.315***	0.410***	−0.002	0.191***	0.277***	0.386***	0.381***
	(−2.01)	(2.70)	(4.97)	(4.90)	(4.25)	(−0.06)	(3.82)	(5.91)	(7.02)	(4.89)
r	0.0261	0.196***	0.336***	0.212***	−0.043	0.002	0.254***	0.344***	0.219***	0.035
	(0.46)	(3.25)	(5.30)	(3.09)	(−0.42)	(0.04)	(4.75)	(6.87)	(3.73)	(0.43)
c	0.046	0.185***	0.223***	0.252***	0.113	0.068	0.137**	0.184**	0.151**	0.131
	(0.63)	(2.37)	(2.72)	(2.83)	(0.85)	(1.02)	(1.98)	(2.84)	(1.99)	(1.22)
Adj. R^2	0.874	0.864	0.843	0.854	0.773	0.894	0.883	0.889	0.882	0.818
	GRS F value: 16.88**					GRS F value: 29.51**				

Note: The table reports the regression results of the CAPM and Fama–French three- and five-factor models by regressing the excess monthly returns of the V/P quintile portfolios against the market excess returns and combinations of SMB, HML, CMA, and RMW factors. Model performance is evaluated using the GRS F statistic. A significant GRS F statistic indicates that the intercepts are jointly different from zero. All the NYSE, AMEX, and NASDAQ stocks in the sample are sorted into five quintile portfolios based on V/P at the end of June each year. V/P is the fundamental value at the end of December of Year t–1, estimated using the previous 5 years' data, divided by the stock price at the end of June of Year t. Q1 consists of stocks with the lowest V/P ratio and Q5 consists of stocks with the highest V/P ratio. R_{it} denotes the monthly return of quintile portfolio i. R_{mt} denotes the monthly returns of the market index, and R_{ft} denotes the monthly risk-free rate on Treasury bills. SMB is the size factor, measured as the return on small stocks minus the return on large stocks. HML is the book-to-market ratio factor, measured as the return on stocks with high B/M ratios minus the return on stocks with low B/M ratios. RMW is the profitability factor, defined as the return on the robust firms (top 30% ranked by operating income) minus the return on the weak stocks (bottom 30% ranked by operating income). CMA is the investment factor, defined as the return on conservative firms (top 30% of firms with the smallest changes in total assets) minus the return on aggressive firms (lowest 30% of firms with the greatest change in total assets). Monthly data for R_{mt}, R_{ft}, SMB, HML, RMW, and CMA were downloaded from Ken French's data library for 276 months over the period 1993–2015.

*, **, and *** denote statistical significance level at 10%, 5%, and 1%, respectively (for two-sided tests). Overlapping returns, in any given Month t, are calculated by holding portfolios formed in the current year (t) as well as in years (t–1) and (t–2). Specifically, overlapping returns for each quantile portfolio is computed as one-third of the first-year returns of the portfolio formed in Year t, one-third of the second-year return of the portfolio formed in Year t–1, and one-third of the third-year return of the portfolio formed in Year t–2.

TABLE 6 | The effect of second and third year returns for quantile portfolios formed on (V/P).

Panel A: One-factor model

	$(R_{it} - R_{ft}) = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \varepsilon_t$ (1)									
	Second year returns					**Third year returns**				
	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
α	0.001	0.001	0.002*	0.003*	0.006***	0.003**	0.002	0.002	0.003*	0.007***
	(1.51)	(1.39)	(1.78)	(1.71)	(2.76)	(2.21)	(1.45)	(1.47)	(1.72)	(3.31)
β	1.109***	1.033***	0.962***	1.090***	1.138***	1.078***	1.022***	0.931***	1.046***	1.128***
	(37.55)	(32.07)	(26.50)	(25.80)	(20.58)	(33.35)	(29.41)	(26.97)	(23.90)	(21.30)
Adj. R^2	0.842	0.796	0.727	0.716	0.616	0.815	0.774	0.743	0.694	0.643
	GRS F value: 8.844					GRS F value: 14.78**				

Panel B: Three-factor model

	$(R_{it} - R_{ft}) = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i\mathrm{SMB}_t + h_i\mathrm{HML}_t + \varepsilon_t$ (2)									
	Second year returns					**Third year returns**				
	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
α	0.001	0.000	0.001	0.001	0.005***	0.002**	0.001	0.000	0.001	0.006***
	(1.38)	(0.81)	(1.25)	(1.20)	(2.80)	(1.99)	(0.81)	(0.70)	(1.04)	(3.27)
β	1.076***	1.034***	0.956***	1.070***	1.079***	1.045***	1.022***	0.930***	1.036***	1.078***
	(38.23)	(36.76)	(34.56)	(35.01)	(25.78)	(34.67)	(33.75)	(35.41)	(32.46)	(25.20)
s	0.262***	0.257***	0.394***	0.537***	0.783***	0.307***	0.274***	0.345***	0.491***	0.661***
	(6.73)	(6.60)	(10.28)	(12.69)	(13.51)	(7.37)	(6.53)	(9.49)	(11.12)	(11.15)
h	0.046	0.339***	0.459***	0.513***	0.476***	0.114***	0.360***	0.446***	0.563***	0.430***
	(1.15)	(8.50)	(11.70)	(11.84)	(8.02)	(2.67)	(8.40)	(11.99)	(12.46)	(7.10)
Adj. R^2	0.865	0.853	0.850	0.860	0.792	0.849	0.839	0.860	0.847	0.781
	GRS F value: 9.352*					GRS F value: 16.76**				

(Continues)

TABLE 6 | (Continued)

Panel C: Five factor model										
	$(R_{it} - R_{ft}) = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i\text{SMB}_t + h_i\text{HML}_t + r_i\text{RMW}_t + c_i\text{CMA}_t + \varepsilon_t$ (3)									
	Second year returns					Third year returns				
	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
α	0.001	0.000	0.000	0.000	0.004***	0.002*	0.000	−0.001	0.000	0.005**
	(1.42)	(0.48)	(0.56)	(0.17)	(2.37)	(1.61)	(0.59)	(1.26)	(0.02)	(2.66)
β	1.069***	1.108***	1.059***	1.134***	1.108***	1.067***	1.110***	1.034***	1.103***	1.121***
	(31.64)	(34.04)	(33.87)	(31.37)	(22.13)	(30.16)	(31.76)	(35.83)	(29.43)	(21.87)
s	0.285***	0.347***	0.488***	0.594***	0.762***	0.268***	0.359***	0.461***	0.569***	0.713***
	(6.48)	(8.18)	(11.97)	(12.59)	(11.66)	(5.79)	(7.84)	(12.20)	(11.60)	(10.63)
h	0.089	0.222***	0.268***	0.391***	0.373***	0.015	0.197***	0.270***	0.452***	0.363***
	(1.57)	(4.03)	(5.09)	(6.40)	(4.42)	(0.26)	(3.34)	(5.53)	(7.12)	(4.18)
r	0.042	0.281***	0.319***	0.195***	−0.016	−0.064	0.281***	0.365***	0.243***	0.161*
	(0.70)	(4.75)	(5.61)	(2.97)	(−0.18)	(−1.01)	(4.42)	(6.96)	(3.57)	(1.73)
c	−0.132*	0.067	0.210***	0.142*	0.251**	0.277***	0.168**	0.138**	0.077	0.037
	(1.68)	(0.88)	(2.88)	(1.69)	(2.15)	(3.37)	(2.07)	(2.05)	(0.89)	(0.31)
Adj. R^2	0.865	0.864	0.868	0.864	0.795	0.856	0.851	0.883	0.853	0.782
	GRS F value: 14.24**					GRS F value: 25.51**				

Note: The table reports the regression results of the CAPM and Fama–French three- and five-factor models by regressing the excess monthly returns of the V/P quintile portfolios against the market excess returns and combinations of SMB, HML, CMA, and RMW factors. Model performance is evaluated using the GRS F statistic. A significant GRS F statistic indicates that the intercepts are jointly different from zero. All the NYSE, AMEX, and NASDAQ stocks in the sample are sorted into five quintile portfolios based on V/P at the end of June each year. V/P is the fundamental value at the end of December of Year t–1, estimated using the previous 5 years' data, divided by the stock price at the end of June of Year t. Q1 consists of stocks with the lowest V/P ratio and Q5 consists of stocks with the highest V/P ratio. R_{it} denotes the monthly return of quintile portfolio i. R_{mt} denotes the monthly returns of the market index, and R_{ft} denotes the monthly risk-free rate on Treasury bills. SMB is the size factor, measured as the return on small stocks minus the return on large stocks. HML is the book-to-market ratio factor, measured as the return on stocks with high B/M ratios minus the return on stocks with low B/M ratios. RMW is the profitability factor, defined as the return on the robust firms (top 30% ranked by operating income) minus the return on the weak stocks (bottom 30% ranked by operating income). CMA is the investment factor, defined as the return on conservative firms (top 30% of firms with the smallest changes in total assets) minus the return on aggressive firms (lowest 30% of firms with the greatest change in total assets). Monthly data for R_{mt}, R_{ft}, SMB, HML, RMW, and CMA were downloaded from Ken French's data library for 276 months over the period 1993–2015.

*, **, and *** denote statistical significance level at 10%, 5%, and 1%, respectively (for two-sided tests). Overlapping returns, in any given Month t, are calculated by holding portfolios formed in the current year (t) as well as in years (t–1) and (t–2). Specifically, overlapping returns for each quantile portfolio is computed as one-third of the first year returns of the portfolio formed in Year t, one-third of the second-year return of the portfolio formed in Year t–1, and one-third of the third year return of the portfolio formed in Year t–2.

TABLE 7 | The effect of dividends for quintile portfolios formed on (V/P).

Panel A: One-factor model

$(R_{it} - R_{ft}) = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \varepsilon_t$ **(1)**

	First year returns					Overlapping returns				
	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
α	0.002**	0.003**	0.002*	0.003*	0.006**	0.003***	0.003***	0.003**	0.004**	0.007***
	(1.97)	(2.18)	(1.65)	(1.93)	(2.32)	(2.83)	(2.70)	(2.46)	(2.52)	(3.30)
β	1.094***	1.096***	1.007***	1.128***	1.269***	1.093***	1.051***	0.969***	1.085***	1.174**
	(39.68)	(34.45)	(26.54)	(25.95)	(21.33)	(42.86)	(34.93)	(28.94)	(27.22)	(22.93)
Adj. R^2	0.851	0.811	0.718	0.709	0.623	0.869	0.816	0.752	0.729	0.656
	GRS F value: 6.703					GRS F value: 13.54**				

Panel B: Three-factor model

$(R_{it} - R_{ft}) = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i\text{SMB}_t + h_i\text{HML}_t + \varepsilon_t$ **(2)**

	First year returns					Overlapping returns				
	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
α	0.002**	0.002*	0.001	0.001	0.004**	0.002***	0.002**	0.002**	0.002**	0.005***
	(2.14)	(1.71)	(0.93)	(1.42)	(2.10)	(2.85)	(2.27)	(2.00)	(2.24)	(3.46)
β	1.051***	1.088***	1.015***	1.099***	1.200***	1.058***	1.048***	0.969***	1.065***	1.116***
	(40.42)	(38.27)	(32.96)	(33.96)	(25.42)	(44.94)	(40.78)	(38.71)	(38.60)	(29.21)
s	0.244***	0.278***	0.329***	0.580***	0.833***	0.271***	0.273***	0.357***	0.538***	0.759***
	(6.78)	(7.06)	(7.71)	(12.90)	(12.71)	(8.30)	(7.67)	(10.29)	(14.04)	(14.31)
h	−0.079**	0.291***	0.495***	0.489***	0.447***	0.026	0.329***	0.463***	0.518***	0.450***
	(−2.16)	(7.19)	(11.29)	(10.62)	(6.66)	(0.79)	(9.00)	(12.99)	(13.19)	(8.28)
Adj. R^2	0.875	0.858	0.825	0.848	0.775	0.895	0.873	0.869	0.877	0.819
	GRS F value: 6.84					GRS F value: 15.04*				

(Continues)

TABLE 7 | (Continued)

Panel C: Five-factor model										
	$(R_{it} - R_{ft}) = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i\text{SMB}_t + h_i\text{HML}_t + r_i\text{RMW}_t + c_i\text{CMA}_t + \varepsilon_t$ (3)									
	First year returns					**Overlapping returns**				
	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
α	0.002*	0.000	−0.001	0.000	0.004*	0.002**	0.000	−0.000	0.001	0.005***
	(1.82)	(0.50)	(−0.78)	(0.19)	(1.95)	(2.53)	(0.81)	(−0.03)	(0.98)	(2.99)
β	1.063***	1.159***	1.124***	1.182***	1.204***	1.067***	1.126***	1.075***	1.136***	1.141***
	(33.90)	(34.64)	(32.01)	(31.10)	(21.18)	(37.64)	(37.88)	(38.80)	(35.13)	(24.82)
s	0.249***	0.331***	0.426***	0.633***	0.811***	0.267***	0.348***	0.460***	0.600***	0.761***
	(6.12)	(7.63)	(9.33)	(12.81)	(10.96)	(7.25)	(9.02)	(12.76)	(14.27)	(12.73)
h	−0.107**	0.151***	0.293***	0.316***	0.411***	−0.003	0.191***	0.276***	0.386***	0.382**
	(−2.03)	(2.68)	(4.94)	(4.92)	(4.28)	(−0.08)	(3.82)	(5.91)	(7.06)	(4.92)
r	0.024	0.195***	0.335***	0.208***	−0.044	0.002	0.252***	0.343***	0.217***	0.033
	(0.43)	(3.23)	(5.27)	(3.03)	(−0.43)	(0.04)	(4.69)	(6.85)	(3.72)	(0.40)
c	0.047	0.185**	0.229***	0.254***	0.114	0.068	0.140**	0.189***	0.152**	0.133
	(0.65)	(2.37)	(2.79)	(2.85)	(0.86)	(1.03)	(2.02)	(2.92)	(2.01)	(1.24)
Adj. R^2	0.874	0.864	0.843	0.855	0.775	0.895	0.882	0.889	0.883	0.819
	GRS F value: 12.67*					GRS F value: 22.84**				

Note: The table reports the regression results of the CAPM and Fama–French three- and five-factor models by regressing the excess monthly returns of the V/P quintile portfolios against the market excess returns and combinations of SMB, HML, CMA, and RMW factors. Model performance is evaluated using the GRS F statistic. A significant GRS F statistic indicates that the intercepts are jointly different from zero. All the NYSE, AMEX, and NASDAQ stocks in the sample are sorted into five quintile portfolios based on V/P at the end of June each year. V/P is the fundamental value at the end of December of Year t–1, estimated using the previous five years' data, divided by the stock price at the end of June of Year t. Q1 consists of stocks with the lowest V/P ratio and Q5 consists of stocks with the highest V/P ratio. R_{it} denotes the monthly return of quintile portfolio i. R_{mt} denotes the monthly returns of the market index, and R_{ft} denotes the monthly risk-free rate on Treasury bills. SMB is the size factor, measured as the return on small stocks minus the return on large stocks. HML is the book-to-market ratio factor, measured as the return on stocks with high B/M ratios minus the return on stocks with low B/M ratios. RMW is the profitability factor, defined as the return on the robust firms (top 30% ranked by operating income) minus the return on the weak stocks (bottom 30% ranked by operating income). CMA is the investment factor, defined as the return on conservative firms (top 30% of firms with the smallest changes in total assets) minus the return on aggressive firms (lowest 30% of firms with the greatest change in total assets). Monthly data for R_{mt}, R_{ft}, SMB, HML, RMW, and CMA were downloaded from Ken French's data library for 276 months over the period 1993–2015.

*, **, and *** denote statistical significance level at 10%, 5%, and 1%, respectively (for two-sided tests). Overlapping returns, in any given Month t, are calculated by holding portfolios formed in the current year (t) as well as in years (t–1) and (t–2). Specifically, overlapping returns for each quantile portfolio is computed as one-third of the first-year returns of the portfolio formed in Year t, one-third of the second-year return of the portfolio formed in Year t–1, and one-third of the third-year return of the portfolio formed in Year t–2.

TABLE 8 | The effect of dividends on second and third year returns for quintile portfolios formed on (V/P).

Panel A: One-factor model

	$(R_{it} - R_{ft}) = \alpha_i + \beta_i(R_{mt} - R_{ft}) + \varepsilon_t$ (1)									
	Second year returns					**Third year returns**				
	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
α	0.003**	0.003**	0.004***	0.004***	0.007***	0.004***	0.003**	0.004**	0.005***	0.008***
	(2.27)	(2.36)	(2.82)	(2.61)	(3.20)	(2.93)	(2.33)	(2.51)	(2.58)	(3.73)
β	1.110***	1.034***	0.963***	1.093***	1.138***	1.079***	1.023***	0.932***	1.048***	1.129***
	(37.52)	(31.73)	(26.49)	(25.88)	(20.53)	(33.41)	(29.33)	(26.97)	(23.98)	(21.33)
Adj. R^2	0.842	0.795	0.727	0.717	0.615	0.816	0.773	0.743	0.695	0.643
			GRS F value: 11.97*					GRS F value: 12.63*		

Panel B: Three-factor model

	$(R_{it} - R_{ft}) = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i\text{SMB}_t + h_i\text{HML}_t + \varepsilon_t$ (2)									
	Second year returns					**Third year returns**				
	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
α	0.002**	0.002**	0.003***	0.003**	0.006***	0.003***	0.002*	0.002**	0.003**	0.007***
	(2.20)	(1.96)	(2.65)	(2.48)	(3.40)	(2.78)	(1.85)	(2.10)	(2.26)	(3.81)
β	1.077***	1.034**	0.957***	1.072***	1.078***	1.046***	1.023***	0.931***	1.038**	1.079***
	(38.19)	(36.76)	(34.65)	(35.18)	(25.74)	(34.75)	(33.65)	(35.54)	(32.71)	(25.29)
s	0.263***	0.259***	0.396***	0.538***	0.786***	0.308***	0.276***	0.348***	0.493***	0.662***
	(6.74)	(6.65)	(10.35)	(12.74)	(13.55)	(7.40)	(6.56)	(9.61)	(11.21)	(11.20)
h	0.045	0.342***	0.461***	0.514***	0.478***	0.115***	0.361***	0.447***	0.563***	0.431***
	(1.13)	(8.55)	(11.76)	(11.89)	(8.04)	(2.69)	(8.38)	(12.06)	(12.54)	(7.14)
Adj. R^2	0.864	0.853	0.851	0.861	0.792	0.850	0.838	0.861	0.849	0.782
			GRS F value: 12.86*					GRS F value: 13.83*		

(Continues)

TABLE 8 | (Continued)

Panel F: Five-factor model										
	$(R_{it} - R_{ft}) = \alpha_i + \beta_i(R_{mt} - R_{ft}) + s_i\text{SMB}_t + h_i\text{HML}_t + r_i\text{RMW}_t + c_i\text{CMA}_t + \varepsilon_t$ (3)									
	Second year returns					**Third year returns**				
	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q1**	**Q2**	**Q3**	**Q4**	**Q5**
α	0.002**	0.000	0.000	0.001	0.005***	0.003**	0.000	0.000	0.001	0.006***
	(2.21)	(0.65)	(0.85)	(1.40)	(2.95)	(2.38)	(0.45)	(0.19)	(1.21)	(3.18)
β	1.069***	1.109***	1.060***	1.137***	1.094***	1.068***	1.110**	1.034***	1.104***	1.121***
	(31.61)	(34.01)	(33.99)	(31.54)	(22.10)	(30.25)	(31.61)	(35.97)	(29.62)	(21.93)
s	0.286***	0.348***	0.489***	0.595***	0.763***	0.268***	0.359**	0.463***	0.569***	0.713***
	(6.42)	(8.19)	(12.03)	(12.65)	(11.68)	(5.81)	(7.82)	(12.30)	(11.65)	(10.65)
h	0.088	0.223***	0.268***	0.391***	0.372***	0.015	0.198**	0.270***	0.452***	0.364***
	(1.60)	(4.04)	(5.09)	(6.42)	(4.43)	(0.26)	(3.33)	(5.55)	(7.17)	(4.21)
r	0.042	0.279***	0.319***	0.196***	−0.011	−0.064	0.277**	0.364***	0.239***	0.158*
	(0.68)	(4.70)	(5.61)	(2.99)	(−0.23)	(−1.01)	(4.33)	(6.95)	(3.52)	(1.70)
c	−0.131*	0.073	0.215***	0.143*	0.237**	0.279***	0.171*	0.141**	0.081	0.038
	(−1.66)	(0.95)	(2.96)	(1.70)	(2.17)	(3.39)	(2.10)	(2.11)	(0.93)	(0.32)
Adj. R^2	0.865	0.864	0.869	0.865	0.795	0.856	0.850	0.884	0.855	0.783
	GRS F value: 12.94*					GRS F value: 20.77**				

Note: The table reports the regression results of the CAPM and Fama–French three- and five-factor models by regressing the excess monthly returns of the V/P quintile portfolios against the market excess returns and combinations of SMB, HML, CMA, and RMW factors. Model performance is evaluated using the GRS F statistic. A significant GRS F statistic indicates that the intercepts are jointly different from zero. All the NYSE, AMEX, and NASDAQ stocks in the sample are sorted into five quintile portfolios based on V/P at the end of June each year. V/P is the fundamental value at the end of December of Year t–1, estimated using the previous 5 years' data, divided by the stock price at the end of June of Year t. Q1 consists of stocks with the lowest V/P ratio and Q5 consists of stocks with the highest V/P ratio. R_{it} denotes the monthly return of quintile portfolio i. R_{mt} denotes the monthly returns of the market index, and R_{ft} denotes the monthly risk-free rate on Treasury bills. SMB is the size factor, measured as the return on small stocks minus the return on large stocks. HML is the book-to-market ratio factor, measured as the return on stocks with high B/M ratios minus the return on stocks with low B/M ratios. RMW is the profitability factor, defined as the return on the robust firms (top 30% ranked by operating income) minus the return on the weak stocks (bottom 30% ranked by operating income). CMA is the investment factor, defined as the return on conservative firms (top 30% of firms with the smallest changes in total assets) minus the return on aggressive firms (lowest 30% of firms with the greatest change in total assets). Monthly data for R_{mt}, R_{ft}, SMB, HML, RMW, and CMA were downloaded from Ken French's data library for 276 months over the period 1993–2015.

*, **, and *** denote statistical significance level at 10%, 5%, and 1%, respectively (for two-sided tests). Overlapping returns, in any given Month t, are calculated by holding portfolios formed in the current year (t) as well as in years (t–1) and (t–2). Specifically, overlapping returns for each quantile portfolio is computed as one-third of the first-year returns of the portfolio formed in Year t, one-third of the second-year return of the portfolio formed in Year t–1, and one-third of the third-year return of the portfolio formed in Year t–2.

The relationship between V/P ratio and long-horizon returns, after controlling for various risk proxies, is also examined. Long-horizon returns (Ret36) are the buy-and-hold returns over 36 months beginning in July of Year t. The risk proxies, including the V/P ratio, are firm characteristics that potentially can explain the cross-section of returns measured over a 3-year period. In other words, these characteristics are candidates in predicting longer than a year buy-and-hold returns at firm level. Equation (4) is estimated using year and industry fixed effects.

$$\begin{aligned}\text{Ret36} = {} & \beta_0 + \beta_1 V/P + \beta_2 \text{Beta} + \beta_3 \text{Ivolatility} + \beta_4 D/M + \beta_5 \text{Ln}\,(\text{ME}) \\ & + \beta_6 \text{Analysts} + \beta_7 \text{Altman's}\, Z + \beta_8 \text{Std}\,(\text{ROA}) + \beta_9 B/M + \varepsilon \quad (4)\end{aligned}$$

If the coefficient of the V/P ratio (β_1) is significantly greater than zero after controlling for various firm characteristics, it indicates that the V/P captures additional risk attributes beyond the ones this study controlled for. In other words, it indicates the V/P anomaly at firm level.

3.3 | Value-to-Price Portfolio Returns and Factor Models

To further examine the risk-based explanation of the V/P effect, we evaluate the returns of V/P-sorted portfolios using the Capital Asset Pricing Model (CAPM) and the Fama and French three- and five-factor models. The objective is to assess whether the five-factor specification provides greater explanatory power for the excess returns of V/P portfolios relative to the three-factor model and the CAPM. First, the CAPM is estimated by regressing monthly excess returns of the V/P quintile portfolios against excess returns of the overall market index (Equation 5a), where R_{it} are monthly equally weighted returns of quintile portfolio i; R_{mt} are monthly returns of the market index; and R_{ft} are the monthly riskless rate on treasury bills.

$$\left(R_{it} - R_{ft}\right) = \alpha_i + \beta_i \left(R_{mt} - R_{ft}\right) + \varepsilon_t \quad (5a)$$

$$\left(R_{it} - R_{ft}\right) = \alpha_i + \beta_i \left(R_{mt} - R_{ft}\right) + s_i \text{SMB}_t + h_i \text{HML}_t + \varepsilon_t \quad (5b)$$

$$\left(R_{it} - R_{ft}\right) = \alpha_i + \beta_i \left(R_{mt} - R_{ft}\right) + s_i \text{SMB}_t + h_i \text{HML}_t + r_i \text{RMW}_t + c_i \text{CMA}_t + \varepsilon_t \quad (5c)$$

Second, Fama and French's three-factor model is assessed by regressing excess returns of the V/P quintile portfolios against excess return on the market index and returns on the Small minus Big size (SMB) and value High minus Low (HML) mimicking portfolios, as outlined in Equation (5b). The SMB and HML B/M mimicking portfolios were formed by independently sorting all stocks in NYSE, AMEX, and NASDAQE into two stock size portfolios (S,B) and three B/M portfolios (L,M,H). Third, a five-factor model is estimated where excess returns of V/P portfolios are regressed against excess returns on the market index and returns on size (SMB), value (HML), profitability (RMW), and investment (Conservative minus Aggressive [CMA]) mimicking portfolios (Equation 5c). Returns on Robust minus Weak (RMW) operating income and CMA investment mimicking portfolios were calculated in similar ways to the returns on the HML portfolio. Finally, the performance of the factor models is compared using the F statistic of Gibbons et al. (1989), or GRS F statistic, as it is known.[35] The null hypothesis of the test proposes that the intercepts α_i are jointly equal to zero. In other words, if the intercept in the regression of V/P portfolio excess returns against the asset pricing factors does not differ from zero, then the asset-pricing model should capture the expected returns of V/P. Otherwise, it indicates the V/P's anomaly at the portfolio level.

4 | Data

The dataset used in this study consists of all AMEX, NYSE, and NASDAQ non-financial firms at the merger of the COMPUSTAT fundamental files, CRSP returns files and Thomson I/B/E/S summary files of analysts' forecasts for 1 year ahead. For a firm to be included in the equity valuation estimate, it must satisfy the following conditions. First, it must have valid data for its book value, net income before extraordinary items, outstanding shares and fiscal year closing price from the fundamental COMPUSTAT files; and 1-year ahead consensus forecasts by financial analysts for earnings per share (EPS) from the Thomson I/B/E/S summary files. Second, the firm must have total assets of at least \$10 million and a closing share price greater than one dollar to mitigate the effect of small companies and to ensure that firms have a stable V/P ratio.[36] Third, firms with negative book value and/or negative consensus in the financial analysts' forecasts for 1 year ahead were deleted from the sample, because including them implied a negative market value (Bryan and Tiras 2007). Finally, the dataset is restricted to firms with a year ending in December to simplify the analysis and to ensure that there was a 6-month gap between the fiscal year end and the portfolios formation date. After applying all filters in the data, the final sample used to estimate fundamental values consisted of 22,873 firm-year observations over the period 1987–2015. Table 1A (Appendix) displays the distribution of firms in the sample by industry and year. Interestingly, the number of observations in the durable goods sectors was the lowest and in business equipment was the highest.

The fundamental value for each firm-year observation is estimated using the previous 5 years of accounting data. At the end of June each year, all stocks are sorted into five portfolios based on the V/P ratio. Portfolio 1 consisted of stocks with the lowest V/P ratio, while stocks with the highest V/P ratio were in Portfolio 5. The fundamental value of December in Year t–1 is matched to the share price for June in Year t to calculate the V/P ratio and form the corresponding portfolios.[37] For a firm to be included in the V/P portfolios, the monthly return data had to be available from July in Year t to June in Year t+1. Monthly returns were collected from the CRSP monthly files for the whole sample period. After matching the estimated fundamental value with the monthly return data, firm-year observations were reduced to 16,580 over the period between 1993 and 2015. For comparability reasons, two additional trading strategies based on B/M and equity market value (size) are considered. Like the V/P trading strategies, at the end of June each year all stocks were sorted by B/M or market equity (ME) into five portfolios. For a stock to be included in the portfolio, the return data had to be available, at least for the next 36 months from the portfolio formation date. Equal weighted returns and size-adjusted ones are calculated across horizons of 1, 2, and 3 years by compounding the monthly return data for each of the quintile portfolios. These and other characteristics, for the sake of comparability, are reported in Table 2.

5 | Results and Discussion

5.1 | Portfolio Returns and Characteristics

Table 1 reports the characteristics of quintile portfolios formed by ME, B/M ratio, and V/P ratio. All firms in the sample are divided into five portfolios at the end of June each year based on one of these measures at a time. Table 1 provides the average ME, B/M, and V/P value for each portfolio, as well as the average post-ranking market beta and the average raw/size-adjusted buy-and-hold returns over the next 12 months (Ret12/SRet12), 24 months (Ret24/SRet24), and 36 months (Ret36/SRet36).[38] The purpose of calculating the size-adjusted buy-and-hold returns is to control for the effect of size differences (ME) among the quintile portfolios. The number of observations for each portfolio is reported in the last row of each panel of Table 1 and applies to all variables except the postestimation returns. The last column of Table 1 reports the postformation returns for the hedge portfolios. Hedge portfolios are formed by taking a long position in Portfolio Q5 and a short position in Portfolio Q1. Statistical significance of the difference (Q5–Q1) is assessed by computing portfolio characteristics on a yearly basis. Finally, time-series variations of the estimated value are used to compute the statistical significance for the mean value over the whole sample period.[39]

Panel A of Table 1 displays that a hedge portfolio, formed by taking a long position in large ME stocks and a short position in small ME stocks, generates average row (size adjusted) buy-and-hold returns of −7.8% (−6.3%), −16.8% (−10.6%), and −28.6% (−15.1%) over 12-, 24-, and 36-months period, respectively. These results indicate that firms with smallest ME mostly outperform firms with largest ME. The portfolio of small stocks has higher beta risk compared to that of large stocks (1.262 vs. 1.003), while their B/M ratios are higher than one indicating that small stocks are price low relative to their book values. Similarly, the V/P ratio for small stocks is higher than two demonstrating that the book value plus the discounted future abnormal earnings is more than twice their market values. Overall, a portfolio of the smallest stocks offers significantly higher returns across all periods, higher valuation metrics (B/M, V/P), and greater systematic (beta) risk than the largest stock portfolio.

Results for the B/M sorted portfolios are reported in Panel B of Table 1. The firms in Q1 (lowest B/M ratio) earn on average raw (size-adjusted) buy-and-hold returns of 13.6% (2.4%) over 1-year horizon, while the firms in Q5 (highest B/M ratio) earn 17.7% (5.4%). The difference of 4.1% (3%) is statistically significant at 5% and comparable in magnitude to the findings of Frankel and Lee (1998). Results also demonstrate that the value (B/M) effect is true especially over longer horizons. For instance, the B/M hedge portfolio (Q5–Q1) generates on average raw (size-adjusted) buy-and-hold returns of 15.6% (10.6%) over the next 36-month period. These findings confirm the B/M effect widely documented in the finance literature (Lakonishok et al. 1994; Asness et al. 2013). Moreover, the similarity in market risk exposure (beta) between high and low B/M portfolios suggests that beta does not explain the return differential between value and glamour stocks. In addition, the V/P ratio is slightly lower than one (0.890) for glamor stocks and slightly higher than two (2.370) for value stocks. In total, the highest B/M stocks yield significantly higher returns, exhibit higher V/P ratios, and display no difference in beta risk exposure compared to the lowest B/M stocks.

Panel C of Table 1 reports returns and characteristics of portfolios sorted by the V/P ratio. Portfolios sorted by V/P closely resemble those sorted by the B/M ratio. Firms in the lowest V/P quintile (Q1) have the lowest B/M ratios, while firms in the highest V/P quintile (Q5) have the highest B/M ratios, indicating that the B/M and V/P ratios are positively correlated. More importantly, a hedge portfolio formed based on the V/P ratio produced average raw (size-adjusted) buy-and-hold returns of 5.3% (3.2%), 13.7% (8.8%), and 27.8% (14.5%) over 12-, 24, and 36-month horizons, respectively. Empirical evidence suggests that the predictive power of the V/P strategy is comparable to that of the B/M strategy in the short term (1-year horizon). However, the performance of the V/P strategy improves substantially over longer horizons relative to the B/M strategy. For instance, the 36-month return of the V/P hedge portfolio was 27.8% (14.5%), compared with 15.6% (10.6%) for the B/M hedge portfolio. Likewise, the market beta is 1.10 for low V/P stocks and 1.28 for high V/P stocks; this small difference in risk exposure cannot fully explain the observed differences in portfolio returns. Interestingly, portfolios with the highest V/P ratios also have the lowest ME. Nonetheless, the size effect accounts for only part of the return differential, and primarily during the first year, as evidenced by the size-adjusted returns. Overall, the V/P effect reported in this study is consistent with findings from previous research (Frankel and Lee 1998; Ali et al. 2003a; Cong et al. 2023).

5.2 | Value-to-Price, Risk Proxies, and Stock Returns

To investigate the relationship between the V/P ratio and risk as well as the V/P and long-horizon returns, various traditional firm risk proxies were used (Frankel and Lee 1998; Ali et al. 2003a). Particularly, the relationship between V/P ratio and firm characteristics is examined using Equation (3).[40] Table 2 reports the Pearson (Spearman) correlation matrix among the V/P and various risk proxies. Results show that the V/P ratio is positively and significantly correlated with B/M, beta, idiosyncratic volatility, long-term debt to ME (D/M) and Std ROA, which indicates that firms with a high V/P ratio also exhibit high firm-specific risk characteristics. In contrast, the strong negative association of V/P with firm size and analyst coverage suggests that mispricing (or risk) is higher among smaller firms and those with low analyst coverage (Hong et al. 2000).

To investigate the risk-based explanation of the V/P effect, Table 3 reports the regression results for Equation (3), estimating two alternative model specifications. In the first one, the V/P ratio is regressed against beta, firm size, and the B/M ratio, following Frankel and Lee (1998). As shown in the first two columns of Table 3, the coefficients on Beta and B/M are positive (0.144

and 0.027, respectively) and statistically significant (t statistics of 8.72 and 6.51, respectively), while the coefficient on Ln(ME) is negative and statistically significant (t statistic of −43.03). These results indicate that firms with high V/P ratios tend to have high B/M ratios, higher beta, and smaller size, whereas firms with low V/P ratio are typically larger, with lower beta and lower B/M ratios. These findings are in line with those of Frankel and Lee (1998). The second specification includes the full set of risk proxies with results reported in the last two columns of Table 3. The coefficients on B/M, idiosyncratic volatility, ROA volatility, and D/M are positive and strongly significant, suggesting that firms with a higher V/P ratio are riskier and likely to command higher expected returns. The negative and significant coefficient on Ln(ME) further indicates that higher V/P ratios are associated with smaller firms, lending support to the risk-based explanation of the V/P strategy. Also, the coefficients on beta, analyst coverage, and Altman's Z score are not consistent with a pure risk explanation of the V/P strategy. Notably, while beta is positive and significant in the first model, it becomes negative and significant in the full model. This result is consistent with the following argument. If stock returns are driven primarily by firm-level news (high idiosyncratic volatility) rather than macroeconomic shocks, their covariance with the market will be low, leading to lower estimated betas. Moreover, if high V/P stocks reflect firm-specific expectations about future cash flows that are largely unrelated to aggregate market cash flows, and if value stocks exhibit significantly higher cash-flow (bad) betas relative to discount-rate (good) betas (Campbell and Vuolteenaho 2004), then an inverse relationship between V/P ratios and market betas would naturally emerge. In addition, the positive coefficient on analyst coverage and the negative sign on Altman's Z score imply that firms with high V/P ratios are less likely to face substantial risk of bankruptcy (Z score) or high liquidity risk (low analyst coverage). Overall, the first model supports a risk-based explanation of the V/P effect, with firm size and beta being highly correlated with the V/P ratio. The full model, nevertheless, suggests that high V/P stocks are primarily characterized by greater idiosyncratic volatility, higher ROA volatility and smaller size. Interestingly, idiosyncratic risk—rather than systematic risk—appears to be more strongly associated with high V/P ratios.[41] Consequently, it remains unclear whether the V/P effect is driven by omitted risk factors.

In addition, the relationship between V/P ratio and long-horizon stock returns is explored after controlling for a range of risk characteristics, as specified in Equation (4). If the coefficient of the V/P ratio (β_1) is significantly greater than zero, conditioning on these risk proxies, it suggests that V/P ratio captures additional sources of risk beyond those explicitly controlled for. Put differently, such evidence supports the existence of a V/P anomaly. Table 4 reports the regression results for three alternative specifications of Equation (4). The first two columns present results from regressing 3-year buy-and-hold returns (Ret36) on the V/P ratio as the sole explanatory variable. The positive and statistically significant coefficient (t statistics 10.23) confirms the presence of the V/P effect in the sample. The second specification, reported in Columns 3–4, augments the model by including beta, Ln(ME) and the B/M ratio. The results demonstrate that firm size and the V/P ratio are strongly negatively and positively associated, respectively, with long-horizon returns. The third specification, reported in the final two columns, includes the full set of variables in Equation (4). The coefficient on the V/P ratio remains positive and statistically significant (t statistics of 1.9), indicating that the V/P effect persists after controlling for a comprehensive set of risk characteristics. This finding suggests that the omission of standard risk proxies is unlikely to explain the V/P effect. Interestingly, the negative and statistically significant relationship between long-run stock returns and beta is further supported by Baker et al. (2011) and Frazzini and Pedersen (2014), who show that low-beta stocks earn higher risk-adjusted returns, while high-beta stocks underperform. Investors face funding constraints, such as leverage constraints and margin requirements, which induce them to overweight high-beta assets instead of using leverage, thereby causing those assets to offer lower returns (see also Christoffersen and Simutin 2017). Bali et al. (2017) also demonstrate that investors' demand for lottery-like stocks is an important driver of the low (high) abnormal returns of stocks with high (low) beta.[42] In addition, several risk characteristics, such as idiosyncratic volatility, size, leverage, and Altman's Z scores, are significantly related to long-term stock returns. For example, the positive relation between idiosyncratic volatility and stock returns is consistent with Stambaugh et al. (2015) who document that the idiosyncratic volatility-return relation is negative among overpriced stocks but positive among underpriced stocks.

5.3 | Value-to-Price Portfolio Returns and Risk Factors

5.3.1 | First-Year and Overlapping Returns

In this section, the relative performance of the CAPM, and the Fama–French three- and five-factor models is assessed in terms of explaining monthly excess returns of V/P-sorted portfolios.[43] The Gibbons, Ross, and Shanken (GRS) statistic for each model are also reported (GRS statistics for each model are also reported. Aharoni et al. (2013) document a positive relation between expected profitability and returns, and a negative one between expected investment and returns. Although expected profitability and investment are significantly positively and negatively related, respectively, to expected returns, their inclusion does not yield an economically meaningful improvement in the explanatory power of the Fama–French model.[44] Golubov and Konstantinidi (2019) examine the value premium using the multiples-based market-to-book decomposition and reveal that the market-to-value component drives the entirety of value strategy return, while the value-to-book component exhibits no return predictability in either portfolio sorts or firm-level regressions. Similarly, Jaffe et al. (2019) find that the mispricing component (market-to-value), but not the growth options component (value-to-book), predicts abnormal returns for up to 5 years and provides incremental information beyond existing asset pricing models.

Goncalves and Leonard (2023) find that the premium associated with the F/M ratio subsumes the B/M ratio premium and has remained relatively stable over time. They further show that the cross-sectional correlation between F/M and B/M has declined, contributing to the apparent attenuation of the traditional value premium. Cong et al. (2023) also document that the V/P ratio, defined as the ratio of RIM-based valuation to market price, subsumes the power of the B/M ratio and generates significant returns after adjusting for common factors. Additionally, Novy-Marx (2013) demonstrates that profitable firms generate significantly higher returns than less profitable firms, despite exhibiting higher valuation ratios. Controlling for profitability substantially enhances the performance of value strategies, particularly among large and liquid stocks.[45] Ball et al. (2020) provide evidence that cash-based operating profitability (a measure that excludes accruals) outperforms measures of profitability that include accruals (gross profitability, operating profitability, and net income). Additionally, cash-based operating profitability (retained earnings-to-market) subsumes accruals (B/M) in predicting the cross section of average returns.

The V/P ratio in this study combines the stock's book value with profitability (abnormal earnings) and is consistent with prior empirical research that either employs a fundamental V/P strategy (Goncalves and Leonard 2023; Cong et al. 2023) or a double-sort strategy based on B/M ratio and gross profitability (Novy-Marx 2013). At the end of each June, stocks are ranked according to their V/P ratio and five portfolios (from lowest to highest V/P) are formed. The monthly returns of these portfolios are recorded until the following June, when portfolios are rebalanced based on the updated V/P stock rankings (first-year returns). Existing empirical evidence, and the results discussed in Section 5.1 reveal that high V/P stocks significantly outperform low V/P stocks for holding periods that extend up to 3 years. For this reason, overlapping returns are also calculated, where in any given month t, the V/P strategy holds a series of portfolios that are selected in the current year (Year t) as well as in the previous 2 years (t–1) and (t–2). Specifically, stocks are selected based on the current year's (Year t) V/P ratio, held for 36 months, while at the same time closing out positions initiated in Year t–3. Under this trading strategy, weights are revised for one-third of the portfolio's securities each year and the remaining positions carry over from the previous 2 years. Finally, given that the selected stocks are held for 3 years, additional results are produced using dividend-adjusted monthly excess returns.

Panel A of Table 5 reports the intercepts and slopes for five V/P quintile portfolios estimated using the CAPM. For first-year returns, the coefficients on the market risk premium are positive and statistically significant for all V/P portfolios, while the intercept is insignificant for four of the five V/P portfolios. Only the highest V/P portfolio exhibits a positive and marginally significant intercept at the 10% level. In the case of overlapping returns, the V/P strategy yields a positive and strongly significant alpha (0.006) for the highest V/P stocks compared with a weakly significant alpha (0.002) for the lowest V/P stocks. Across both first-year and overlapping returns, portfolio loadings on the market risk premium generally increase from low- to high-V/P stocks, although the relationship is not strictly linear and displays a U-shaped pattern.

The results of the Fama–French three-factor model are reported in Panel B of Table 5. The coefficients on the market, size, and B/M factors are positive and significant across the V/P portfolios, with the exception of the HML loading of the lowest V/P portfolio, which is negative and significant. Loadings on the size factor increase monotonically from low to high V/P portfolios, while loadings on the market exhibit a U-shaped pattern similar to that observed under the CAPM. Notably, the highest V/P portfolio exhibits only the third-highest loading on the value factor. The significance of the factor loadings indicates that variation in V/P excess returns across quintile portfolios is associated with differences in firm size, B/M ratios, and market betas. In contrast, the intercepts (alphas) of the three-factor model are positive but statistically insignificant across all V/P portfolios.

For overlapping returns, monthly excess returns are largely explained by exposure to the market, size, and value factors, yielding generally insignificant alphas across most V/P portfolios. However, the highest V/P portfolio exhibits a positive and statistically significant alpha of 0.004, indicating that the Fama–French three-factor model does not fully capture the variation in excess returns for high V/P stocks. Moreover, the highest V/P portfolio consistently exhibits greater loadings on the market and size factors than the lowest V/P portfolio, while its loading on the B/M factor does not follow the same pattern, ranking only third highest among the quintiles.

The highly significant alpha for the highest V/P portfolio corresponds to a risk-adjusted annual return of approximately 5.6% and underscores the importance of holding high V/P stocks beyond the first year. To further investigate this result, two additional risk proxies—profitability and investment—are examined in addition to the market, size, and value factors (Hou et al. 2015; Fama and French 2015).

Panel C of Table 5 reports the intercepts and slopes from the five-factor model. This model adds profitability and investment factors to the Fama–French three-factor model. Novy-Marx (2013) identifies a proxy for expected profitability that is strongly related to average returns, while Aharoni et al. (2013) document a weaker but statistically reliable relation between investment and average return. For first-year returns, the coefficients on the five risk factors are positive and statistically significant in most of the cases. In particular, the market, size, and B/M factors are positively related to V/P portfolio excess returns with factor loadings showing an increasing, but not strictly monotonic pattern across portfolios. The coefficients on the profitability (RMW) and investment (CMA) factors are positive and statistically significant only for the middle V/P portfolios (Q2, Q3, and Q4). Interestingly, the profitability and investment factors do not appear to explain excess returns of the highest and lowest V/P portfolios. Novy-Marx (2013) shows that stocks with high B/M ratios and high gross profitability earn higher returns. Given that the V/P ratio effectively augments the B/M ratio by adding the present value of future abnormal profits in the numerator, the highest V/P portfolio appears to select firms for which profitability and investment premiums are not realized in the first year. Overall, the results suggest that variation in V/P excess returns is primarily driven by differences in market beta, firm size, and B/M ratios, while operating profitability and investment contribute only marginally to explaining the excess returns of the intermediate Portfolios Q2, Q3, and Q4.[46] The alphas from the five-factor model are not statistically different from zero across the V/P quintiles, with the exception of Portfolio Q3, which exhibits a significant negative alpha. When overlapping returns are considered, a similar pattern emerges with respect to factor loadings. Nevertheless, extending the holding period beyond 12 months generates a significant positive alpha (0.004) for the highest V/P portfolio. This corresponds to an annualized risk-adjusted return of approximately 4.9% and highlights the importance of longer holding horizons in capturing the V/P effect.

A comparison of the GRS F statistics across the three models indicates that the five-factor model outperforms both the CAPM and the traditional Fama–French three-factor model. The performance of the four-factor model (unreported), which excludes the B/M factor, is very similar to the five-factor model.[47] Overall, V/P excess returns vary with differences in market betas, firm size, and B/M ratios, operating profitability and investment across quintile portfolios, consistent with the findings of Hou et al. (2015) and Fame and French (2015). Notably, the loadings on the five factors are not evenly increasing from low to high V/P stocks. Finally, although profitability and investment provide additional explanatory power across V/P portfolio returns, the five-factor model does not fully account for the variation in excess returns, particularly for portfolios with high V/P ratios.

5.3.2 | The Effect of Second- and Third-Year Returns

In the previous section, overlapping returns performed significantly better than first-year returns after risk. This means that holding stocks that were selected based on the V/P ranking of the previous 2 years contributes additional excess returns to the V/P portfolios. Consequently, interest is turned on the performance of V/P portfolios during the second- and third-year holding periods. As reported in Table 6, second- and third-year returns load positively on the market factor, with a U-shaped pattern similar to that observed for first-year returns. The CAPM alpha is strongly positive (at 1%) for the highest V/P portfolio and only weekly positive (at 10%) for the second- and third-highest V/P portfolios (Q3, Q4). For third-year returns, significant positive alphas are observed for both the highest and lowest V/P portfolios (0.007 and 0.003, respectively). Under the Fama–French three-factor model, the market, size, and B/M factors have significant positive effects on second- and third-year returns, with only the size factor exhibiting a clear increasing pattern from low- to high-V/P portfolios. Specifically, for second-year returns, a significant alpha of 0.005 is observed for the highest V/P portfolio, while for third-year returns, alphas are significantly positive for both the highest and lowest V/P portfolios (0.006 and 0.002, respectively). In other words, the highest V/P portfolios correspond to annual risk-adjusted excess returns of 6.2% and 7.4% in Years 2 and 3, respectively.

Regressing second- and third-year returns on the five factors produces positive and significant loadings on the market, size, and B/M factors. Second-year returns are positively related to the profitability factor for portfolios with V/P ratio close to one (Q2, Q3, and Q4), and although this effect is weak, it extends to the highest V/P stocks when third-year returns are considered. The investment factor loads positively on second-year returns for Portfolios Q3, Q4, and Q5, whereas its positive impact on third-year returns appears concentrated in Portfolios Q1, Q2, and Q3. The highest V/P portfolio exhibits positive loadings on the investment and profitability factors during the second and third years, respectively, a pattern that differs from first-year and overlapping returns. Importantly, the investment and profitability factors have a significant positive impact on the lowest and highest V/P portfolios, respectively, despite showing no relation to first-year and overlapping returns.[48] The alphas for second and third-year returns are significantly positive only for the highest V/P stocks indicating that holding periods beyond the first year generate meaningful risk-adjusted returns. Specifically, monthly alphas of 0.004 and 0.005 are observed for the highest V/P portfolio in Years 2 and 3, respectively, after accounting for all five risk factors proposed in Fama and French (2015). These results suggest that the highest V/P portfolio selects firms that are significantly mispriced relative to their equity and expected profitability growth. For example, the highest V/P stocks continue to deliver significant risk-adjusted excess returns despite positive loadings on the investment factor in Year 2 and on the profitability factor in Year 3. Overall, the second- and third-year performance of the highest V/P portfolio helps explain the difference observed between first-year and overlapping returns.

5.3.3 | The Effect of Dividends

Chen et al. (2008) show that the expected value premium, defined as the sum of the difference in expected dividend-price ratios and the difference in expected long-run dividend growth rates between value and growth portfolios, averages 6.1% per year. This premium consists of an expected dividend growth component of 4.4% and an expected dividend-price ratio component of 1.7%, indicating that the majority of the value premium is attributed to dividend growth. In the case of overlapping returns, stocks are held for 3 years, and so, V/P portfolio returns are adjusted for dividends. Results for first-, second-, and third-year dividend-adjusted returns are reported in Table 7.

Empirical findings reported in Panel A of Table 7 show that the coefficients on the market risk premium are positive and significant for all V/P portfolios. Loadings on the market factor exhibit the same U-shaped pattern observed before adjusting portfolio returns for dividends. For first-year returns, the alphas are positive and statistically significant at the 5% and 10% levels, with the highest alpha observed for the highest V/P portfolio. In contrast, before adjusting for dividends, first-year alphas were not statistically significant. For overlapping returns, the V/P strategy yields positive and strongly significant alphas across all V/P portfolios. Specifically, the highest V/P portfolio generates an alpha of 0.007, while the lowest V/P portfolio produces an alpha of 0.003. Notably, after accounting for dividends, CAPM alphas are significant across all V/P portfolios, whereas in the case of non-dividend-adjusted returns, alpha is significant only for the highest V/P portfolio.

Turning to the Fama–French three-factor model (Panel B of Table 7), the coefficients on the market, size, and B/M factors are positive and significant for all V/P portfolios. These results confirm that variation in V/P excess returns is associated with differences in firm size, B/M ratios, and market betas across quintile portfolios. Specifically, the highest V/P portfolio consistently exhibits higher loadings higher on the size factor than the lowest V/P portfolio, while its loading on B/M ranks only third among the quintiles. Similar factor loadings are obtained for the overlapping returns.

For first-year returns, the three-factor model produces positive and significant alphas (at the 5% level) only for the highest and lowest V/P portfolios. In contrast, for overlapping returns, positive and significant alphas are observed across all V/P portfolios, with the largest alpha (0.005) recorded for the highest

V/P portfolio. The highly significant alphas across V/P portfolios imply that risk-adjusted annual returns as high as 6.5% can be earned. Dividend adjustments substantially enhance the alphas for overlapping returns, while for first-year returns, positive and significant alphas are confined to portfolios at the extreme ends of the V/P distribution. Notably, when simple (non-dividend-adjusted) returns are used, the three-factor model alphas are insignificant.

Panel C of Table 7 reports the intercepts and slopes for the five-factor model. For first-year returns, the market, size, and value factors are positively related to V/P portfolio returns, with factor loadings demonstrating an increasing—but not strictly monotonic—pattern from low to high V/P portfolios. In addition, the coefficients on the profitability (RMW) and investment (CMA) factors are positive and significant only for the middle V/P portfolios (Q2, Q3, and Q4). In contrast, profitability and investment factors do not appear to explain the excess returns of the highest and lowest V/P portfolios for either first-year or overlapping returns. The alphas from the five-factor model are positive and weakly significant for Portfolios Q1 (low V/P) and Q5 (high V/P). For overlapping returns, a similar pattern is observed with respect to factor loadings; however, the alphas become strongly significant, with the highest (lowest) V/P portfolio generating a monthly excess return of 0.5% (0.2%). Excluding the HML factor from the five-factor model, empirical results (unreported) reveal that both profitability and investment load positively and significantly for the highest V/P portfolio, while alphas remain strongly significant. Finally, adjusting returns for dividends yields positive and strongly (weakly) significant alphas in the case of overlapping (first-year) returns, while, in the case of simple returns (non-dividend-adjusted), significant alphas are observed only for overlapping returns.

Adjusting second and third-year returns for dividends produces highly significant alphas across all V/P portfolios under both the CAPM and the Fama–French three-factor model (Table 8). Factor loadings remain largely unchanged.[49] Furthermore, high V/P portfolios generate significantly higher risk-adjusted returns than low V/P both in Years 2 and 3. In contrast, under the five-factor model, alphas are significant only for the two extreme V/P portfolios. For example, low V/P portfolios yield monthly excess return of 0.2% (0.3%), compared with 0.5% (0.6%) for high V/P portfolios in the second (third) year. Within the five-factor model, the market, size, and value factors continue to exert a significant positive impact on monthly excess returns. Similarly, the profitability factor loads positively and significantly for the intermediate V/P Portfolios Q2, Q3, and Q4. Importantly, the highest V/P stocks load positively on the investment risk factor in the second year, whereas, in the third year, this positive exposure shifts to the lowest V/P stocks. Finally, adjusting returns for dividends yields significant risk-adjusted excess returns in both the second and third years, particularly for high V/P stocks, reinforcing the conclusion that second- and third-year returns contribute substantially to the overlapping returns.

Overall, forming portfolios formed on the basis of the V/P ratio and held for more than a year generate significant risk-adjusted excess returns in the second and third years. Alphas become economically and statistically significant when the holding period exceeds 1 year, with third-year alphas slightly larger than those in the second-year and concentrated among stocks with the highest V/P ratios. Dividend-adjusted returns in the second and third years exhibit a similar pattern in factor loadings, while the resulting alphas are generally larger and more statistically significant than those obtained using simple (non-dividend-adjusted) returns.

6 | Conclusion

The superior performance of value investing strategies is a well-established empirical fact (Lakonishok et al. 1994; Asness et al. 2013). Value strategies involve investing in stocks that appear cheap or have low market prices relative to fundamentals such as earnings, dividends, or book values. The finance literature primarily relies on the B/M ratios to identify value stocks, whereas the accounting literature introduces the V/P ratio, in which a firm's intrinsic value is estimated using the residual income valuation model (Frankel and Lee 1998; Ali et al. 2003a; Goncalves and Leonard 2023; Cong et al. 2023). Frankel and Lee (1998) show that a V/P-based strategy outperforms simple market-multiple approaches and generates abnormal returns over longer horizons.[50] Frankel and Lee (1998) and Ali et al. (2003a) argue that the predictive ability of V/P strategy is most likely attributable to market mispricing. In contrast, Hwang and Lee (2013) suggest that the mispricing explanation of the V/P anomaly is premature and warrants further investigation. Motivated by the these findings, this paper examines, first, whether investments in high V/P (B/μ) stocks outperform investments in low V/P (B/μ) stocks, second, the relationship between V/P ratios, long-run returns, and various risk characteristics at firm level and, third, whether standard asset pricing models can account for the excess return of V/P-sorted portfolios (Hou et al. 2015; Fama and French 2015). Overall, the study aims to examine the relative importance of risk versus mispricing explanations of the value premium using portfolios sorted by the V/P ratio. To address these questions, we construct a comprehensive dataset by merging COMPUSTAT, CRSP, and I/B/E/S for all non-financial firms listed on AMEX, NYSE, and NASDAQ over the period 1987–2015.

Results show that high V/P portfolios consistently outperform low V/P portfolios. A hedge portfolio formed on the V/P ratio yields, on average, raw (size adjusted) buy-and-hold returns of 5.3% (3.2%), 13.7% (8.8%), and 27.8% (14.5%) over the next 12-, 24-, and 36-month horizons, respectively. The predictive power of the V/P strategy is comparable to that of the B/M strategy in the short term (i.e., 1-year horizon). However, the performance of the V/P strategy improves significantly over longer horizons compared with that of the B/M strategy. For example, over a 36-month period, the V/P hedge portfolio generates raw (size-adjusted) returns of 27.8% (14.5%), compared with only 15.6% (10.6%) for the corresponding B/M hedge portfolio. Importantly, portfolios with the highest V/P ratios also exhibit the lowest market value of equity. Nevertheless, the size effect accounts for only part of the return differential, primarily within the first year. Overall, the V/P effect documented here is highly consistent with prior evidence reported in studies such as Frankel and Lee (1998), Ali et al. (2003a), Goncalves and Leonard (2023), and Cong et al. (2023).

To examine whether the V/P ratio captures economically meaningful information about expected returns, this study examines the relationship between the V/P ratio, long-run returns, and various firm characteristics commonly used as proxies for risk, including market beta, size, B/M ratio, idiosyncratic volatility, earnings variability, leverage, bankruptcy risk, and analyst coverage. The findings reveal a positive and statistically significant association between the V/P ratio and idiosyncratic volatility, earnings variability, and leverage, and a negative relation with size and beta. These results suggest that firms with high V/P ratios tend to exhibit greater firm-specific rather than systematic risk, which may justify the mispricing explanation through limited arbitrage (Shleifer and Vishny 1997). Importantly, the relationship between long-run stock returns and the V/P ratio is positive and statistically significant, while the effect of firm size (idiosyncratic volatility) and beta (earnings variability) on returns is negative (positive) and statistically significant. These results are consistent with prior evidence showing that the value effect is stronger among stocks with higher idiosyncratic volatility, smaller size and lower beta risk (Ali et al. 2003b; Frazzini and Pedersen 2014).

The study further examines whether the Fama–French five-factor model explains the excess returns of the V/P strategy. For first-year (post portfolio formation) returns, the estimated factor loadings are positive and statistically significant, while the alphas are not significantly different from zero. Specifically, the market, size and value factors are positively related to V/P portfolio excess returns, with factor loadings displaying an increasing, but not monotonic, pattern from low to high V/P portfolios. The coefficients on the profitability (RMW) and investment (CMA) factors are positive and significant only for the V/P portfolios in the middle (Q2, Q3, and Q4). Interestingly, the profitability and investment factors do not explain excess returns of the highest and lowest V/P portfolios. As shown in Novy-Marx (2013), stocks with high B/M ratios and high gross profitability earn high returns. Since the V/P ratio can be viewed as augmenting the numerator of the B/M ratio with the present value of future abnormal profits, portfolios with the highest V/P ratios consist of firms for which profitability and investment premia are not realized within the first year. For overlapping returns, factor loadings are similar to those observed for 1-year returns, while statistically significant alphas emerge only for portfolios with the highest V/P ratios. Holding portfolios for more than 12 months (overlapping returns) generates an annual risk-adjusted return of 4.9% for the highest V/P stocks, raising questions about the importance of second- and third-year returns. Indeed, forming portfolios on the basis of V/P ratio and holding them for beyond 1 year, yields substantial risk-adjusted excess returns in Years 2 and 3, with third-year alphas slightly exceeding those in the second-year, primarily among the highest of the V/P portfolios.[51]

Overall, V/P portfolio returns are largely explained by exposure to standard risk factors, yet these factors do not fully account for the variation in excess returns. The highest V/P portfolios appear to select firms whose future profitability and investment growth are underestimated by the market. In essence, the V/P ratio captures information about the timing and persistence of future fundamentals that is not immediately incorporated into prices. Adding to this argument, the strong second- and third-year performance of the highest V/P portfolio largely explains the difference between first-year and overlapping returns.

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Endnotes

[1] Existing empirical evidence suggests that high value-to-price stocks significantly outperform low value-to-price stocks for holding periods that extend up to 3 years. One explanation of this slow price convergence is the speed at which long-term fundamental information is incorporated in stock prices. An alternative explanation of the value-to-price effect is that it reflects cross-sectional risk differences. In addition, the predictive power of the V/P strategy is comparable to that of the B/M strategy in the short term (1-year horizon). However, the performance of the V/P strategy significantly improved over longer horizons in comparison with those of the B/M.

[2] Their findings suggest that the power to predict the returns of the V/P strategy is attributable to market mispricing and this mispricing is subsequently corrected during earnings announcement periods when a substantial amount of accounting information reaches the market. To explore the risk hypothesis as an alternative explanation of the V/P anomaly, Ali et al. (2003a) control for a large set of risk characteristics similar to Gebhardt et al. (2001) and Gode and Mohanram (2003).

[3] The intrinsic value (V) is estimated using the residual income model (Ohlson 1995; Dechow et al. 1999) and the V/P factor is constructed as a mimicking portfolio based on the V/P ratio similarly to their original factors.

[4] This prediction is consistent with the observation that high V/P stocks typically exhibit high idiosyncratic volatility and low betas. Elevated firm-specific risk may constrain arbitrage, while limited exposure to systematic cash-flow risk (low bad beta) suggests that conventional factor models may fail to fully price these securities, thereby contributing to the persistence of abnormal returns (Shleifer and Vishny 1997; Ali et al. 2003b; Campbell and Vuolteenaho 2004; Frazzini and Pedersen 2014).

[5] Diversification eliminates only the component of firm-level volatility that is cross-sectionally uncorrelated. To the extent that high V/P firms share exposure to common but unmodeled economic shocks, their "idiosyncratic" volatility may reflect omitted systematic risk. In such a setting, portfolio formation will not fully eliminate this component, and the associated return premium may be consistent with a risk-based explanation.

[6] Fama and French (2015, 2016) used the dividend discount model to explain why profitability and investment add to the description of average returns provided by book-to-market (B/M) ratio. They found that the five-factor model largely explains the cross-sectional return patterns (related to size, B/M, profitability, and investment), the value factor becomes redundant for describing average returns, and several return anomalies shrink. Hou et al. (2015) show that an empirical q factor model consisting of the market factor, a size factor, an investment factor, and a profitability factor largely summarizes the cross section of average stock returns.

[7] Frankel and Lee (1998) clarify that their implementation of V/P strategies is simple, and it focuses on a valuation model based on analysts' forecasts. They suggest that future research may adopt different valuation approaches that refine the model parameters. Frankel and Lee (1998) and Ali et al. (2003a) used merely the financial analysts' forecasts in calculating the fundamental value, while Hwang and Lee (2013) fundament value estimates depend only on historical data.

[8] If the coefficient of the V/P ratio is significantly greater than zero after controlling for risk characteristics, it indicates that the V/P captures additional risk factors beyond the ones controlled for. In other words, it demonstrates the value-to-price anomaly at firm level.

[9] The performance of the factor models is assessed using the Gibbons-Ross-Shanken (GRS) F statistic. Sentana (2009) provides a survey of mean-variance efficiency tests, while Penaranda and Sentana (2015), Barillas and Shanken (2018), and Kelly et al. (2019) propose different frameworks for comparing assets pricing models and testing portfolio efficiency.

[10] Investors overreact to stocks that have performed strongly (poorly) in the past and buy (sell) them, so that these stocks become overpriced (underpriced). A value strategy buys the underpriced stocks and sells the overpriced ones, thus outperforming the market. The overreaction story is also consistent with DeBondt and Thaler (1985). However, Fama and French (1992) find that investors in value (high book-to-market) stocks earn higher average returns as a compensation to higher fundamental risk. Fama and French (1993) show that small and high book-to-market firms offer higher returns as a compensation for higher systematic risk associated with distress (more sensitive to business cycle and credit condition changes).

[11] Novy-Marx (2013) demonstrates that profitable firms generate significantly higher returns than unprofitable firms, despite having significantly higher valuation ratios. Controlling for profitability significantly increases the performance of value strategies, especially among the largest, most liquid stocks. These results are difficult to reconcile with popular explanations of the value premium, as profitable firms are less prone to distress, have longer cash flow durations, and have lower levels of operating leverage. Ball et al. (2016, 2020) reveal that cash-based operating profitability (a measure that excludes accruals) outperforms measures of profitability that include accruals (gross profitability, operating profitability, and net income). In addition, cash-based operating profitability (retained earnings-to-market) subsumes accruals (book-to-market) in predicting the cross section of average returns.

[12] For 12-month horizons, the value-to-price (V/P) ratio predicts cross-sectional returns as well as the book-to-market ratio (B/M). However, over 2 or 3-year periods, buy-and-hold returns from V/P strategies are more than twice those from B/M strategies. Thus, the V/P trading strategy is more successful and leads to higher abnormal returns than simple market multiples do.

[13] Dechow et al. (1999) adopt variations of the residual income model (Ohlson 1995), which include incorporating both historical earning information and other information (or ignoring other information) and other alternatives which restrict the persistence parameters of abnormal earnings and other information either to zero or to unity in different combinations. One year ahead financial analysts' forecasts are used as a proxy for "other information" variables.

[14] Although this finding is consistent with market inefficiency, the authors claim they cannot rule out the possibility that the predictive power of V/P arises from time-varying expected returns. Even after accounting for well-known determinants of such risk, V/P may still capture a previously unidentified dimension of time-varying risk.

[15] For instance, Lo and Lys (2000) argue that adding analysts' forecasts of earnings beyond 1 year has no significant impact on the correlation between intrinsic value and price. They claim that analysts' forecasts tend to be noisier after the first year and impounding them in residual income valuation model has insignificant effect. Instead, most of the cross-sectional correlation between price and value is primarily attributed to the book value of equity and to a lesser extent to the first year's earnings. The conclusions of Lo and Lys (2000) are in line with those of Myers (1999). An alternative argument may be that if the discount rate used to calculate the intrinsic value were too low, giving rise to high V/P, it is inevitable to obtain higher realized returns than another firm with a low V/P.

[16] Their findings suggest that the power of the V/P strategy to predict returns is attributable to market mispricing and this mispricing is subsequently corrected during earnings announcement periods, since a substantial amount of accounting information reaches the market after earnings announcement dates. Interestingly, they observe that the V/P ratio is significantly positively associated with future abnormal returns after controlling for known risk factors, including the book-to-market ratio, market beta, Altman's Z score, the implied cost of capital and the debt-to-equity ratio.

[17] Moreover, Wei and Zhang (2007) use different measures of arbitrage risk (accrual quality, divergence of opinion, investor sophistication, firm age, idiosyncratic volatility, liquidity, institutional ownership) and find that when stocks with any of these risks in the highest quintiles are excluded from analysis, the profitability of V/P strategies improves significantly. Their evidence confirms the view that there are limits to arbitrage in that high fundamental risk, high noise trader risk, and high transaction costs deter arbitrage activities and therefore prolong the process of stock prices to converge to their fundamental values and lower the arbitrage returns. This also provides support to the Shleifer and Vishny (1997) finding that when market prices diverge far from fundamental values, the arbitrage becomes ineffective.

[18] Equally, Jaffe et al. (2019) demonstrate that the market-to-value component, but not the value-to-book one, predicts abnormal returns for up to 5 years and provides incremental information relative to existing asset pricing models.

[19] They state that if risk is the underlying reason for the V/P anomaly, then the abnormal returns of this strategy should be concentrated in the portfolio of stocks that remain in the extreme V/P portfolios. However, if mispricing is the underlying reason for the V/P anomaly, then the abnormal returns of the V/P strategy should be concentrated in the subsample of stocks in the extreme V/P portfolios that display price convergence. Their empirical evidence supports the mispricing explanation of the V/P anomaly and suggests that analysts' forecast revisions are not the driving force of price discovery for the portfolio of stocks that exhibit price convergence.

[20] For example, Frankel and Lee (1998) note that the V/P anomaly could still be due to unidentified risk factors other than book-to-market, firm size, and market beta. Kothari (2001) argues that the V/P strategy is quite puzzling because it generates low abnormal returns in the first year and a half, but substantially larger abnormal returns for the next year and a half. Beaver (2002) claims that it is challenging to resolve the contradiction between the rapid market reaction to new information, which implies market efficiency, with the persistence of abnormal returns for 3 years after forming portfolios (the V/P anomaly is an example), which implies that market inefficiency is responsible.

[21] Also, Daniel and Titman (1997) investigate whether portfolios with similar characteristics but different loadings on the Fama and French (1993) factors have different returns. Once they control for firm characteristics, expected returns do not appear to be positively related to the loadings on the market, book-to-market, or size factors. Similarly, Gregory et al. (2001, 2003) highlight that there are substantial differences in returns between value and glamour portfolios that cannot be explained by their loading on the Fama–French factors. Fama and French (2006) show no significant difference in the value premiums of large-cap and smaller stocks, and once they control for size and book-to-market expected returns do not seem to be related to CAPM betas. Petkova and Zhang (2005) provide evidence that value (growth) portfolio betas tend to covary positively (negatively) with the expected market risk premium, but their covariance is far too small to explain the observed magnitude of the value premium within the conditional CAPM.

[22] Petkova (2006) demonstrates that shocks to the aggregate dividend yield, term spread, default spread, and 1-month Treasury-bill yield explain the cross section of average returns better than the Fama–French model. When the innovations in the predictive variables are present in the model, loadings on HML and SMB lose their explanatory power for the cross-section of returns. More, the value factor proxies for a term spread surprise factor in returns, while size factor proxies for a default spread surprise factor.

[23] This result lends support to the view that the reward for holding high book-to-market (B/M) stocks arises at least partly because of true non-diversifiable risk. Kang et al. (2011) use a conditional version of the

consumption CAPM and show that value stocks are riskier than growth stocks in bad times, supporting the risk-based story.

[24] The value-to-price (V/P) ratio is equivalent to adding the present value of future abnormal profits on the numerator of the book-to-market (B/M) ratio assuming the residual income model is used to derive the intrinsic value of a stock.

[25] In contrast to Feltham and Ohlson (1995), Myers (1999) does not differentiate between operating assets and financial assets because (a) it is difficult, if not impossible, to separate the financial assets from the operating assets and (b) residual operating income and residual income are equal since the financial assets earn only the normal income.

[26] A constant is included in the abnormal income forecasting equation and in the valuation equation because abnormal income on average may be different from zero.

[27] Therefore, parameter estimates from the valuation equations account for the effect of allowing regression errors from each of the forecasting equations to be correlated with those in the valuation equation. For detailed information on the estimation of a set of SUR equations with panel data see Avery (1977), Baltagi (1980), Kinal and Lahiri (1990), and Biorn (2004).

[28] This study used 5 years of data such that the estimated parameters reflect the trade-off between efficiency and stationarity. The efficiency of the estimate would improve by increasing the number of years, but the parameters are likely to become nonstationary. Also, Fama and French's industry classification is used, and the sample is divided into 12 sectors.

[29] For example, the intrinsic/fundamental value V of Firm A in 2010, is the value MV_{it} predicted from the valuation Equation (1d) using estimated coefficients from the valuation equation and all firms' data except Firm A's in year 2010. Since firm's A data in 2010 are not used to estimate the coefficients, the predicted value is considered to be out-of-sample. To generate a prediction for Firm A in year 2010 imposing the residual income model's structure, we estimate Equations (la)–(1d) using the data for all firms except Firm A in year 2010 and restricting the coefficients in Equation (1d) to equal those implied by Equations (la)–(1c). Moreover, to generate a prediction for Firm A in year 2010 without imposing the model's structure, we estimated Equation (1d) using the data for all firms except Firm A in year 2010.

[30] This must be positive ($\omega_{12} > 0$) if residual income is driven in part by understated book value instead of monopolistic power. BV will be negatively related to future abnormal earnings if the normal return on equity book value is less than the return assumed in the empirical tests. Including the equity book value in the abnormal earnings equation allows the effects of conservatism to manifest (Feltham and Ohlson 1995; Ashton and Wang 2015) and relaxes the assumption that the cost of capital associated with calculating abnormal earnings is a predetermined cross-sectional constant. Separate industry estimation of all equations permits the level of conservatism and, at least partially, the cost of capital associated with abnormal earnings to vary by industry.

[31] This must satisfy the following conditions, $1 < \omega_{22} < (1 + r)$, for a going concern.

[32] The approach of Dechow et al. (1999) requires the cost of capital (r) and abnormal income persistency parameter (ω_{11}) to be estimated before (υ). Thus, the accuracy of (υ) depends on the accuracy of both (r) and (ω_{11}).

[33] The value of 1a–1d equation parameters, using all data, on average, are ω_{11}= 0.732, ω_{12}= 0.017, ω_{13}= 0.426, ω_{22} = 1.05, ω_{33}= 0.56, α_1= 1.88, α_2 = 0.71, and α_3= 2.88. Results are comparable with previous studies (Barth et al. 2005; Dechow et al. 1999; Ohlson 1995; Wang 2013).

[34] This allows intercepts to vary across industries and years but restricts slope coefficients to be the same. For panel data sets that have more firms than years, a common estimation approach is to include dummy variables for each time period (to absorb the time effect) and then cluster by firm or industry (to treat the firm/industry effect). The parametric approach only works when the dependence is correctly specified, and the firm/time effects are fixed. However, if the precise form of dependence is not known, a less parametric approach may be preferred and a solution is to cluster on two dimensions (e.g., firm, time) simultaneously, given a sufficient number of clusters exists (Petersen 2009).

[35] Sentana (2009) provides a survey of mean-variance efficiency tests, while Penaranda and Sentana (2015) propose a unifying framework for the empirical evaluation of asset pricing models. Moreover, Barillas and Shanken (2018) and Kelly et al. (2019) use a Bayesian framework and Instrumental PCA methods, respectively, to compare asset pricing models.

[36] Frankel and Lee (1998) claim that firms with stock price of less than one dollar are characterized by an unstable V/P ratio and poor market liquidity.

[37] To ensure that accounting variables are known before returns are computed, we allow a minimum gap of 3 months between the fiscal-year-end and the portfolio formation date. Specifically, we match accounting data for all fiscal year ends in the calendar Year t–1 to returns on portfolios formed at the end of June of Year t. This approach is consistent with handling market and accounting data in the literature (Fama and French 1992).

[38] The post-market beta for each firm is calculated by regressing the market index against the contemporaneous firm-monthly returns over the next 36 months. The size-adjusted buy-and-hold returns were calculated as the difference between the raw buy-and-hold returns and the corresponding CRSP size-decile index returns.

[39] The procedure proposed by Newey and West (1987) was used to correct for the serial correlation in buy-and-hold returns which was induced by overlapping the holding periods beyond the first year (Ret24/SRet24 and Ret36/SRet36).

[40] The B/M ratio is included as a proxy for firm growth, while Beta and Ivolatility capture the systematic and non-systematic risks of stock variability. Size and Analysts were used to capture the differences in the information environment and their impact on the risks perceived among small and large firms. In addition, Altman's Z score is included to capture the risk of financial distress, the D/M ratio captures the influence of firm leverage, and the standard deviation of ROA (Std ROA) is a proxy of firms' earning variability.

[41] This result is consistent with Ali et al. (2003b), who find that the value (B/M) effect is stronger among stocks with higher idiosyncratic volatility. If the value effect reflects mispricing driven by systematic biases in expectations about future earnings, an important question is why such mispricing is not rapidly eliminated by professional arbitrageurs. Shleifer and Vishny (1997) argue that strategies aimed at exploiting mispriced assets are both risky and costly—particularly when prices deviate substantially from fundamental values—thereby limiting arbitrage activity and allowing mispricing to persist over time. Consequently, stocks with greater idiosyncratic volatility, and hence higher arbitrage risk, should be more susceptible to persistent mispricing that is not corrected by arbitrageurs.

[42] More recent evidence shows that a betting against beta (BAB) strategy gives more (less) pronounced returns in low(high)-volatility states (Barroso et al. 2025), insignificant alphas when we control for co-skewness (Schneider et al. 2020), and low returns if transaction costs and standard procedures in estimating betas and the BAB factor are used (Novy-Marx and Velikov 2022). Boloorforoosh et al. (2020) develop a conditional CAPM model with stochastic beta, that comoves with market variance and the stochastic discount factor, and show that beta risk explains expected returns on low- and high-beta stocks.

[43] Petkova (2006) reveals that shocks to the aggregate dividend yield, term spread, default spread, and 1-month Treasury-bill yield explain the cross section of average returns better than the Fama–French model. Hahn and Lee (2006) also demonstrate that the size and value premiums

are compensations for higher exposure to the risks related to changing credit market conditions, default spread, and interest rates, term spread, respectively.

[44] The authors conclude that any benefit from adding expected profitability and expected investment to size, and B/M is limited to picking the bottom performing four percent of firms.

[45] These results are difficult to reconcile with popular explanations of the value premium, as profitable firms are less prone to distress, have longer cash flow durations, and have lower levels of operating leverage.

[46] The effect of the HML falls slightly across the V/P portfolios when the investment and profitability factors are added. This is also consistent with Aharoni et al. (2013) who find a reduction in the coefficient on book-to-market (B/M) ratio when expected investment (growth in equity) is added as an explanatory variable of excess returns. B/M and expected investment are potentially driven by similar economic forces and an improvement in one can be at the expense of the other.

[47] Fama and French (2015) display that the value factor of the FF three-factor model becomes redundant for describing average return with the addition of profitability and investment factors (GRS F statistic of the four-factor model is higher than the five-factor one). Excluding the HML factor from the five-factor model, the first-year return results (unreported) reveal that the investment factor becomes positive and significant for the highest V/P portfolio, while, in the case of overlapping returns, both profitability and investment are positive and significant for the same portfolio. Four-factor model alphas are not significant for first-year returns but significant positive for the overlapping ones.

[48] The loading on the value factor is significant negative for the lowest V/P stocks for first-year returns. Low V/P stocks resemble growth firms in terms of low book-to-markets and negative HML loadings. The lowest V/P stocks do not load on HML during Year 2 and load positively on HML during Year 3. However, considering the five-factor model, the lowest of the V/P stocks do not load on the value and profitability factors during Years 2 and 3, while the loading on the investment factor is weak negative and strong positive in Years 2 and 3, respectively. The negative loading on the investment factor is consistent with the negative effect of expected investment on returns especially for high growth (and potential low V/P) stocks (Aharoni et el. 2013). The performance of the low V/P stocks during Year 3 seems to resemble that of conservative rather than aggressive investment stocks. This is also consistent with the behaviour of growth firms seeking to finance investment initially through equity and later via debt.

[49] This means that the size (market) factor displays an increasing (U-shape) pattern from low to high V/P stocks during both years, while the B/M factor has the second (third) highest effect on the second (third) year returns of the highest V/P stocks.

[50] One explanation of this slow price convergence is the speed at which long-term fundamental information is incorporated in stock prices. An alternative explanation of the value-to-price effect is that it reflects cross-sectional risk differences.

[51] For example, the highest V/P stocks offer a significant risk adjusted (excess) return despite loading positively on the investment factor in Year 2 and on the profitability factor in Year 3. Importantly, the second- and third-year performance of the highest V/P stocks explains the difference between the first-year and overlapping returns. Adjusting second- and third-year returns for dividends, a similar pattern on the effect of the risk factors is obtained, while the observed alphas are slightly higher and more significant than the case of simple returns, across all years and V/P portfolios.

[52] Residual income is defined as the difference between the investors' expected income and the required income, where the required income is calculated as forecast book equity at the start of each period multiplied by the cost of equity capital.

[53] Thus, the market value calculation is based on a 3-year horizon, as shown below: $MV_t = BV_t + \frac{(\mathrm{FROE}_t - r)}{(1+r)} BV_t + \frac{(\mathrm{FROE}_{t+1} - r)}{(1+r)^2} BV_{t+1} + \frac{(\mathrm{FROE}_{t+2} - r)}{(1+r)^2 r} BV_{t+2}$ where BV_{t+k} is the forecast book value of equity at the end of Year $t+k$, $k = 1, 2$, or 3; FROE_{t+k} is the forecast return on equity for Year $t+k$, $k = 1, 2$, or 3; and r is the estimated cost of equity capital.

[54] Two alternative approaches to estimate FROE_t are used. The first approach is based on the earnings in the previous period, while the second is based on I/B/E/S analysts' forecasts. To estimate the former, the authors use return on equity for period t to proxy for all three future returns on equity (FROE_{t+k}). To estimate the latter, they use 1-year-ahead, 2-year-ahead consensus I/B/E/S earnings-per-share forecasts, and a 5-year long-term earnings growth rate in earnings.

[55] Other information represents any relevant information other than accounting information. According to Ohlson (1995), other information in the next period ($t+1$) is a linear function of other information from the current period (t).

[56] Book value of equity is used as a benchmark to calculate normal returns and, consequently, residual income, as shown in Equation (A1).

[57] Myers (1999) maintains that intrinsic value calculation as implemented by Frankel and Lee in one part of their model, often implies arbitrage. Therefore, he proposes a framework for modifying linear information dynamics while preserving the internal consistency of the model.

[58] Altman′s Z= 1.2 × (Working Capital/Total Assets) + 1.4 × (Retained Earnings/Total assets) + 3.3 × (EBIT/Total Assets) + 0.6 × (Market Value of Equity/Book Value of Total Liabilities) + 1.0 × (Sales/Total assets)

References

Aharoni, G., B. Grundy, and Q. Zeng. 2013. "Stock Returns and the Miller Modigliani Valuation Formula: Revisiting the Fama French Analysis." *Journal of Financial Economics* 110: 347–357.

Ali, A., L. Hwang, and M. A. Trombley. 2003a. "Residual-Income-Based Valuation Predicts Future Stock Returns: Evidence on Mispricing Vs. Risk Explanations." *The Accounting Review* 78, no. 2: 377–396.

Ali, A., L. Hwang, and M. A. Trombley. 2003b. "Arbitrage Risk and the Book-to-Market Anomaly." *Journal of Financial Economics* 69: 355–373.

Altman, E. I. 1968. "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy." *The Journal of Finance* 23, no. 4: 589–609.

Ashton, D., and P. Wang. 2015. "Conservatism in Residual Income Models: Theory and Supporting Evidence." *Accounting and Business Research* 45, no. 3: 387–410.

Asness, C. S., T. J. Moskowitz, and L. H. Pedersen. 2013. "Value and Momentum Everywhere." *The Journal of Finance* 68: 929–985.

Avery, R. B. 1977. "Error Components and Seemingly Unrelated Regressions." *Econometrica* 45: 199–209.

Baker, M., B. Bradley, and J. Wurgler. 2011. "Benchmarks as Limits to Arbitrage: Understanding the Low-Volatility Anomaly." *Financial Analysts Journal* 67: 40–54.

Bali, T. G., S. Brown, S. Murray, and Y. Tang. 2017. "A Lottery Demand-Based Explanation of the Beta Anomaly." *Journal of Financial and Quantitative Analysis* 52, no. 6: 2369–2397.

Ball, R., J. Gerakos, T. J. Linnainmaa, and V. Nikolaev. 2016. "Accruals, Cashflows, and Operating Profitability in the Cross Section of Stock Returns." *Journal of Financial Economics* 121: 28–45.

Ball, R., J. Gerakos, T. J. Linnainmaa, and V. Nikolaev. 2020. "Earnings, Retained Earnings, and Book-to-Market in the Cross Section of Expected Returns." *Journal of Financial Economics* 135: 231–254.

Baltagi, B. H. 1980. "On Seemingly Unrelated Regressions With Error Components." *Econometrica* 48: 1547–1551.

Barillas, F., and J. Shanken. 2018. "Comparing Asset Pricing Models." *The Journal of Finance* 73, no. 2: 715–754.

Barroso, P., A. Detzel, and P. Maio. 2025. "The Volatility Puzzle of the Beta Anomaly." *Journal of Financial Economics* 165: 1–16.

Barth, M. E., W. H. Beaver, J. R. Hand, and W. R. Landsman. 1999. "Accruals, Cash Flows, and Equity Values." *Review of Accounting Studies* 4, no. 3-4: 205–229.

Barth, M. E., W. H. Beaver, J. R. Hand, and W. R. Landsman. 2005. "Accruals, Accounting-Based Valuation Models, and the Prediction of Equity Values." *Journal of Accounting, Auditing & Finance* 20, no. 4: 311–345.

Barth, M. E., and A. P. Hutton. 2004. "Analyst Earnings Forecast Revisions and the Pricing of Accruals." *Review of Accounting Studies* 9: 59–96.

Beaver, W. H. 2002. "Perspectives on Recent Capital Market Research." *The Accounting Review* 77, no. 2: 453–474.

Biørn, E. 2004. "Regression Systems for Unbalanced Panel Data: A Stepwise Maximum Likelihood Procedure." *Journal of Econometrics* 122: 281–291.

Boloorforoosh, A., P. Christoffersen, M. Fournier, and C. Gouriéroux. 2020. "Beta Risk in the Cross-Section of Equities." *The Review of Financial Studies* 33, no. 9: 4318–4366.

Brennan, M. J., N. Jegadeesh, and B. Swaminathan. 1993. "Investment Analysis and the Adjustment of Stock Prices to Common Information." *Review of Financial Studies* 6, no. 4: 799–824.

Brennan, M. J., and A. Subrahmanyam. 1995. "Investment Analysis and Price Formation in Securities Markets." *Journal of Financial Economics* 38, no. 3: 361–381.

Bryan, D. M., and S. L. Tiras. 2007. "The Influence of Forecast Dispersion on the Incremental Explanatory Power of Earnings, Book Value, and Analyst Forecasts on Market Prices." *The Accounting Review* 82, no. 3: 651–677.

Campbell, J. Y., and T. Vuolteenaho. 2004. "Bad Beta, Good Beta." *The American Economic Review* 94, no. 5: 1249–1275.

Chen, L., R. Petkova, and L. Zhang. 2008. "The Expected Value Premium." *Journal of Financial Economics* 87, no. 2: 269–280.

Christoffersen, S. E. K., and M. Simutin. 2017. "On the Demand for High-Beta Stocks: Evidence From Mutual Funds." *Review of Financial Studies* 30, no. 8: 2596–2620.

Cong, L. W., N. D. George, and G. Wang. 2023. "RIM-Based Value Premium and Factor Pricing Using Value-Price Divergence." *Journal of Banking and Finance* 149: 1–22.

Daniel, K., and S. Titman. 1997. "Evidence on the Characteristics of Cross-Sectional Variation in Stock Returns." *The Journal of Finance* 52, no. 1: 1–33.

De Bondt, W. F. M., and R. Thaler. 1985. "Does the Stock Market Overreact?" *The Journal of Finance* 40: 793–805.

Dechow, P. M., A. P. Hutton, and R. G. Sloan. 1999. "An Empirical Assessment of the Residual Income Valuation Model." *Journal of Accounting and Economics* 26: 1–34.

Dechow, P. M., and R. G. Sloan. 1997. "Returns to Contrarian Investment Strategies: Tests of Naive Expectations Hypotheses." *Journal of Financial Economics* 43: 3–27.

Fama, E. F., and K. R. French. 1992. "The Cross-Section of Expected Stock Returns." *The Journal of Finance* 47, no. 2: 427–465.

Fama, E. F., and K. R. French. 1993. "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics* 33, no. 1: 3–56.

Fama, E. F., and K. R. French. 1995. "Size and Book-to-Market Factors in Earnings and Returns." *The Journal of Finance* 50, no. 1: 131–155.

Fama, E. F., and K. R. French. 1997. "Industry Costs of Equity." *Journal of Financial Economics* 43, no. 2: 153–193.

Fama, E. F., and K. R. French. 2006. "Profitability, Investment, and Average Returns." *Journal of Financial Economics* 82, no. 3: 491–518.

Fama, E. F., and K. R. French. 2015. "A Five-Factor Asset Pricing Model." *Journal of Financial Economics* 116, no. 1: 1–22.

Fama, E. F., and K. R. French. 2016. "Dissecting Anomalies With a Five-Factor Model." *Review of Financial Studies* 29, no. 1: 69–103.

Feltham, G. A., and J. A. Ohlson. 1995. "Valuation and Clean Surplus Accounting for Operating and Financial Activities." *Contemporary Accounting Research* 11, no. 2: 689–731.

Frankel, R., and C. M. Lee. 1998. "Accounting Valuation, Market Expectation, and Cross-Sectional Stock Returns." *Journal of Accounting and Economics* 25, no. 3: 283–319.

Frazzini, A., and L. H. Pedersen. 2014. "Betting Against Beta." *Journal of Financial Economics* 111, no. 1: 1–25.

Gallant, R. A. 1975. "Seemingly Unrelated Nonlinear Regressions." *Journal of Econometrics* 3: 35–50.

Gebhardt, W. R., C. Lee, and B. Swaminathan. 2001. "Toward an Implied Cost of Capital." *Journal of Accounting Research* 39, no. 1: 135–176.

Gibbons, M. R., S. A. Ross, and J. Shanken. 1989. "A Test of the Efficiency of a Given Portfolio." *Econometrica* 57: 1121–1152.

Gode, D., and P. Mohanram. 2003. "Inferring the Cost of Capital Using the Ohlson–Juettner Model." *Review of Accounting Studies* 8, no. 4: 399–431.

Golubov, A., and T. Konstantinidi. 2019. "Where Is the Risk in Value? Evidence From a Market-to-Book Decomposition." *The Journal of Finance* 74, no. 6: 3135–3186.

Gonçalves, A. S., and G. Leonard. 2023. "The Fundamental-to-Market Ratio and the Value Premium Decline." *Journal of Financial Economics* 147: 382–405.

Gregory, A., R. D. F. Harris, and M. Michou. 2001. "An Analysis of Contrarian Investment Strategies in the UK." *Journal of Business Finance and Accounting* 28, no. 9: 1131–1228.

Gregory, A., R. D. F. Harris, and M. Michou. 2003. "Contrarian Investment and Macroeconomic Risk." *Journal of Business Finance and Accounting* 30, no. 1: 213–255.

Hahn, J., and H. Lee. 2006. "Yield Spreads as Alternative Risk Factors for Size and Book-to-Market." *Journal of Financial and Quantitative Analysis* 41, no. 2: 245–269.

Hong, H., T. Lim, and J. C. Stein. 2000. "Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies." *The Journal of Finance* 55, no. 1: 265–295.

Hou, K., C. Xue, and L. Zhang. 2015. "Digesting Anomalies: An Investment Approach." *Review of Financial Studies* 28, no. 3: 650–705.

Hwang, L., and W. Lee. 2013. "Stock Return Predictability of Residual-Income-Based Valuation: Risk or Mispricing?" *Abacus* 49, no. 2: 219–241.

Jaffe, F. J., J. Jindra, J. D. Pedersen, and T. Voetmann. 2019. "Can Mispricing Explain the Value Premium?" *Financial Management* 49: 615–633.

Johnson, W. B., and S. Xie. 2004. "The Convergence of Stock Price to Fundamental Value." SSRN Working Paper No. 590542.

Kang, J., T. S. Kim, C. Lee, and B. Min. 2011. "Macroeconomic Risk and the Cross-Section of Stock Returns." *Journal of Banking and Finance* 35, no. 12: 3158–3173.

Kelly, B. T., S. Pruitt, and Y. Su. 2019. "Characteristics Are Covariances: A Unified Model of Risk and Return." *Journal of Financial Economics* 134: 501–524.

Kinal, T., and K. Lahiri. 1990. "A Computational Algorithm for Multiple Equation Models With Panel Data." *Economics Letters* 34: 143–146.

Kothari, S. 2001. "Capital Markets Research in Accounting." *Journal of Accounting and Economics* 31, no. 1: 105–231.

Lakonishok, J., A. Shleifer, and R. W. Vishny. 1994. "Contrarian Investment, Extrapolation, and Risk." *The Journal of Finance* 49, no. 5: 1541–1578.

Lazzati, N., and A. A. Menichini. 2018. "A dynamic model of firm valuation." *The Financial Review* 53, no. 3: 499–531.

Lee, C., J. Myers, and B. Swaminathan. 1999. "What Is the Intrinsic Value of the Dow?" *The Journal of Finance* 54, no. 5: 1693–1741.

Lee, C. M., and B. Swaminathan. 1999. "Valuing the Dow: A Bottom-Up Approach." *Financial Analysts Journal* 55, no. 5: 4–23.

Lettau, M., and S. Ludvigson. 2001. "Resurrecting the (C)CAPM: A Cross-Sectional Test When Risk Premia Are Time-Varying." *Journal of Political Economy* 109: 1238–1287.

Lo, K., and T. Lys. 2000. "The Ohlson Model: Contribution to Valuation Theory, Limitations, and Empirical Applications." *Journal of Accounting, Auditing & Finance* 15, no. 3: 337–367.

McElroy, M. B., and E. Burmeister. 1988. "Arbitrage Pricing Theory as a Restricted Nonlinear Multivariate Regression Model." *Journal of Business and Economic Statistics* 6, no. 1: 29–42.

Myers, J. N. 1999. "Implementing Residual Income Valuation With Linear Information Dynamics." *The Accounting Review* 74, no. 1: 1–28.

Newey, W. K., and K. D. West. 1987. "Hypothesis Testing With Efficient Method of Moments Estimation." *International Economic Review* 28, no. 3: 777–787.

Novy-Marx, R. 2013. "The Other Side of Value: The Gross Profitability Premium." *Journal of Financial Economics* 108: 1–28.

Novy-Marx, R., and M. Velikov. 2022. "Betting Against Betting Against Beta." *Journal of Financial Economics* 143: 80–106.

Ohlson, J. A. 1990. "A Synthesis of Security Valuation Theory and the Role of Dividends, Cash Flows, and Earnings." *Contemporary Accounting Research* 6: 648–676.

Ohlson, J. A. 1995. "Earnings, Book Values and Dividends in Security Valuation." *Contemporary Accounting Research* 11: 661–687.

Ohlson, J. A. 2001. "Earnings, Book Values, and Dividends in Equity Valuation: An Empirical Perspective." *Contemporary Accounting Research* 18, no. 1: 107–120.

Peasnell, K. V. 1982. "Some Formal Connections Between Economic Values and Yields and Accounting Numbers." *Journal of Business Finance & Accounting* 9, no. 3: 361–381.

Peñaranda, F., and E. Sentana. 2015. "A Unifying Approach to the Empirical Evaluation of Asset Pricing Models." *The Review of Economics and Statistics* 97, no. 2: 412–435.

Petkova, R. 2006. "Do the Fama-French Factors Proxy for Innovations in Predictive Variables." *The Journal of Finance* 61, no. 2: 581–612.

Petersen, M. A. 2009. "Estimating Standard Errors in Finance Panel Data Sets: Comparing Approaches." *Review of Financial Studies* 22, no. 1: 435–480.

Petkova, R., and L. Zhang. 2005. "Is Value Riskier Than Growth?" *Journal of Financial Economics* 78: 187–202.

Piotroski, J. D., and E. C. So. 2012. "Identifying Expectation Errors in Value/Glamour Strategies: A Fundamental Analysis Approach." *Review of Financial Studies* 25: 2841–2875.

Pope, P. F., and P. Wang. 2005. "Earnings Components, Accounting Bias and Equity Valuation." *Review of Accounting Studies* 10, no. 4: 387–407.

Schneider, P., C. Wagner, and J. Zechner. 2020. "Low-Risk Anomalies?" *The Journal of Finance* 75, no. 5: 2673–2718.

Sentana, E. 2009. "The Econometrics of Mean-Variance Efficiency Tests: A Survey." *Econometrics Journal* 12: 65–101.

Shleifer, A., and R. W. Vishny. 1997. "The Limits of Arbitrage." *The Journal of Finance* 52, no. 1: 35–55.

Stambaugh, R. F., J. Yu, and Y. Yuan. 2015. "Arbitrage Asymmetry and the Idiosyncratic Volatility Puzzle." *The Journal of Finance* 70, no. 5: 1903–1948.

Tsay, R. S., Y. Lin, and H. Wang. 2008. "Residual Income, Value-Relevant Information, and Equity Valuation: A Simultaneous Equations Approach." *Review of Quantitative Finance and Accounting* 31, no. 4: 331–358.

Tsay, R. S., Y. Lin, and H. Wang. 2009. "Residual Income, Non-Earnings Information, and Information Content." *Journal of Forecasting* 28, no. 6: 487–511.

Wang, P. 2013. "The Role of Disaggregation of Earnings in Stock Valuation and Earnings Forecasting." *Accounting and Business Research* 43, no. 5: 530–557.

Wei, J. K., and J. Zhang. 2007. "Arbitrage Risk and Arbitrage Returns: Evidence From the Fundamental Value-to-Price Anomaly." SSRN Working Paper No. 1108868.

Xu, L. 2007. "Is V/P a Distinct Anomaly?" *Review of Accounting and Finance* 6, no. 4: 404–418.

Zellner, A. 1962. "An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias." *Journal of the American Statistical Association* 57: 348–368.

Appendix A

A.1 Theoretical Development of the Residual Income Valuation Model

The most popular accounting-based approach used to predict firm value is the Residual Income Model (RIM) developed Peasnell (1982), Ohlson (1990, 1995), and Feltham and Ohlson (1995). According to the RIM model, the value of any firm can be expressed as a function of its current year book value plus the present value of expected future residual income[52] as shown below,

$$MV_t = BV_t + \sum_{T=1}^{\infty} R^{-T} E_t \left(NI_{t+T}^a \right) \tag{A1}$$

where MV_t is the market value of equity at date t; BV_t is the book value of equity at date t; R is 1 plus r (r is the cost of equity capital); $E_t[.]$ is the expectation operator based on information available at time t; NI_t is the net income for period t; and NI_t^a is the residual income defined as $NI_t - r \times BV_{t-1}$. Frankel and Lee (1998) use the residual income model by simplifying the valuation technique in a short horizon and assuming that, after the third year, the forecasted residual income will be earned in perpetuity.[53] Their empirical implementation of the residual income model requires to estimate the future book value of equity and the future return on equity for the next 3 years.[54] Frankel and Lee's implementation of residual income model (1998) differs from the original implementation by Ohlson (1995) and Dechow et al. (1999). Ohlson (1995) argues that a firm's ability to generate residual income is driven by its monopolistic power. However, this monopolistic power will diminish after several years due to competition in the market, residual income will shrink, and the returns earned by the firm will be equal to the cost of capital. To capture this process, an autoregressive process can be used to model and forecast abnormal earnings.

According to Ohlson's linear information dynamics, the abnormal income in the period t+1 is a linear function of the abnormal income in the current period and other information (ν).[55] Thus, Ohlson's linear information model can be expressed using Equation (A2).

$$NI_{it}^a = \omega NI_{it-1}^a + \nu_{it-1} + \varepsilon_{1,it} \tag{A2a}$$

$$\nu_{it} = \gamma \nu_{it-1} + \varepsilon_{2,it} \tag{A2b}$$

$$MV_{it} = BV_{it} + \alpha_1 NI_{it}^a + \alpha_2 \nu_{it} + u_{it} \tag{A2c}$$

$$\alpha_1 = \frac{\omega}{[1 + r - \omega]}$$

$$\alpha_2 = \frac{1 + r}{(1 + r - \omega) \times (1 + r - \gamma)}$$

where ν_{it} is other information; $\varepsilon_{1,it}$, $\varepsilon_{2,it}$, and u_{it} are error terms; i and t subscripts refer to the firm and year, respectively; and ω and γ are the persistence parameters and should be non-negative and less than one. Feltham and Ohlson (1995) argue neither that accounting measures of performance are neutral nor that competitive power will over time drive residual income to zero, as proposed by Ohlson (1995). On the contrary, accounting practices, and particularly accounting conservatism, cause the book value of equity to differ systemically from the market value of equity. In other words, accounting conservatism influences the residual income series in the long run, because it understates the book value of equity.[56] Thus, Feltham and Ohlson (1995) suggest a second linear information process in which the book value of equity is used as a proxy of conservatism. Myers (1999) emphasizes that the key contribution of Ohlson (1995) and Feltham and Ohlson (1995) stems from their linear information dynamics. He argues that ad hoc modifications of these linear information dynamics, as in Frankel and Lee (1998) and Dechow et al. (1999), could violate the internal consistency of the model.[57]

Similarly, Ohlson (2001) contends that ignoring other information variable (υ) or equating it to zero, as proposed by Dechow et al. (1999), could be of empirical interest. However, these propositions drastically shrink the empirical content of the linear information model. More importantly, Ohlson (2001) states that it is plausible to use a consensus of analysts' forecasts (f_t) for period t+1 as a proxy for expected earnings, based on all available information at period t, and hence to calculate the other information variable (υ). According to Dechow et al. (1999) and Ohlson (2001), the other information variable (υ) can be calculated as follows.

$$\upsilon_t = E_t \left[NI_{t+1}^a \right] - \omega \cdot NI_t^a \tag{A3}$$

$$E_t \left[x_{t+1}^a \right] = f_t^a = f_t - r \cdot BV_t$$

$$\upsilon_t = f_t^a - \omega \cdot NI_t^a$$

where $E_t[NI_{t+1}^a]$ is the conditional expectation of abnormal income for the period t+1 based on all information available at period t; f_t is the consensus of analysts' forecasts of expected earnings for period t+1; and ω is the persistence parameter of abnormal income and is estimated by ignoring other information variable of Equation (A2a).

A.2 Risk Proxies

This section outlines the definition, measurement and economic intuition behind each firm characteristic that we use as a proxy for risk.

Beta: This is a measure of systematic risk. Beta is estimated for each firm-year by implementing the capital asset pricing model (CAPM). Previous studies have documented a positive relationship between a firm's specific Beta and future stock returns (Fama and French 1992; Frankel and Lee 1998; Ali et al., 2003b). We use the CRSP value weighted index as a proxy for market returns. We estimated firm-specific Betas at the end of December each year by regressing the monthly returns of each firm against the contemporaneous monthly returns of the CRSP value-weighted index using the previous 36 months of data. In other words, to estimate the Beta of firm i for Year t, we use firm i's monthly returns over the period from January $t-3$ to December t.

Ivolatility: This is a measure of unsystematic or idiosyncratic risk. Unsystematic risk for each firm-year is calculated as follows. First, we regressed the daily return data for the previous year at the end of December each year against the contemporaneous daily returns of the CRSP value weighted index. Second, we used the variance of the residuals from the previous regression as a proxy of Ivolatility. Several previous empirical studies have documented an association between future stocks returns and idiosyncratic risk (Ali et al. 2003a; Gebhardt et al. 2001; Gode and Mohanram 2003).

D/M: This is a measure of leverage in the firm. Several prior studies have suggested a positive association between a firm's future stocks returns and its leverage ratio (Fama and French 1992; Gebhardt et al. 2001; Gode and Mohanram 2003). For every year, we measured D/M as the ratio of the book value of long-term debt at the end of December of the previous year to the market capitalization at the end of June in the current year.

Ln(ME): This is a measure of firm size. Several previous studies use firm size as a proxy of the information environment. It is argued that the information environment is influenced by several interrelated factors such as trading volume, bid-ask spreads, firm size, and institutional investors (Barth and Hutton 2004). It is expected that firms with a better information environment have a lower risk premium because it reduces the information asymmetry between the firm and investors (Ali et al. 2003a). It is well documented that size is correlated with the differences in information environment that lead to a lower risk for large firms than for small firms (Gebhardt et al. 2001; Gode and Mohanram 2003). For the purposes of this study, size is measured as the log of firm i's market value at the end of June in Year t. A negative association between the risk premium and firm size is expected.

Analysts: They are a measure of the financial analysts' coverage of the firm. It is another measure of the information environment. For instance, Brennan et al. (1993) argue that a firm with better coverage from financial analysts responds faster to market information than those with inferior analysts' coverage. Furthermore, analysts' coverage can be used as a proxy of firm liquidity. For instance, Brennan and Subrahmanyam (1995) argue that firms with better analysts' coverage tend to be more liquid than those with inferior analysts' coverage. Therefore, we used the number of analysts' estimates included in the I/B/E/S database in May of Year t as a proxy for liquidity and information environment. We expected a negative association between firms with better analyst coverage and future stock returns.

Altman′s Z: This is a measure of financial distress. It is measured as a bankruptcy score, from Altman's (1968) model.[58] We expect a positive association between Altman's Z score and future stock returns.

Std(ROA): This is a measure of earnings variability. Several previous studies have argued that the variability of earnings is likely to reflect intrinsic cash flow risks and is considered a main source of risk for firm valuations (Gebhardt et al. 2001; Gode and Mohanram 2003). For the purposes of this paper, Std(ROA) is calculated as the standard deviation of returns on assets in the past 5 years.

B/M: This is a measure of the book to market ratio. It has been argued that B/M can be used as a proxy for accounting conservatism, the growth opportunities of a firm, or perceived risk (Fama and French 1992; Lakonishok et al. 1994). It is very difficult to distinguish empirically between various interpretations of B/M and to predict the direction of the relationship between the B/M ratio and future stock returns. For the purposes of this paper, it is calculated as the book value of equity at the end of December of the previous year divided by the market value of equity at the end of June in the current year.

A.3 Number of Observations by Year and Industry

The sectors are defined as follows:

1. Non-dur.—Consumer non-durables—food, tobacco, textiles, apparel, leather, toys (SIC code: 0100–0999, 2000–2399, 2700–2749, 2770–2799, 3100–3199, and 3940–3989)
2. Dur.—Consumer durables—cars, TV's, furniture, household appliances (SIC code: 2500–2519, 2590–2599, 3630–3659, 3710–3711, 3714-3714, 3716-3716, 3750–3751, 3792-3792, 3900–3939, and 3990–3999)
3. Manufac.—Manufacturing—machinery, trucks, planes, office furniture, paper, com printing (SIC code: 2520–2589, 2600–2699, 2750–2769, 3000–3099, 3200–3569, 3580–3629, 3700–3709, 3712–3713, 3715-3715, 3717–3749, 3752–3791, 3793–3799, 3830–3839, and 3860–3899)
4. Energy—oil, gas, and coal extraction and products (SIC code: 1200–1399 and 2900–2999)
5. Chemical—chemicals and allied products (SIC code: 2800–2829 and 2840–2899)
6. Equip.—business equipment, computers, software, and electronic equipment (SIC code: 3570–3579, 3660–3692, 3694–3699, 3810–3829, and 7370–7379)
7. Telecom—telephone and television transmission (SIC code: 4800–4899)
8. Utility—utilities (SIC code: 4900–4949)
9. Retail—wholesale, retail and some services, for example, laundries, repair shops (SIC code: 5000–5999, 7200–7299, and 7600–7699)
10. Health—healthcare, medical equipment and drugs (SIC code: 2830–2839, 3693-3693, 3840–3859, and 8000–8099)
11. Other—other mines, construction, build material, transportation, hotels, business services, entertainment.

TABLE A1 | Number of observations by year and industry.

Year	Non-dur.	Dur.	Manufac.	Energy	Chemical	Equip.	Telecom	Utility	Retail	Health	Other	Total
1987	22	12	41	14	14	31	5	34	12	15	41	241
1988	23	12	41	14	13	33	5	37	13	18	46	255
1989	23	12	43	19	14	35	5	37	13	20	48	269
1990	23	10	46	18	17	37	7	42	14	23	48	285
1991	23	10	54	21	17	37	8	43	15	25	49	302
1992	25	13	57	21	18	44	8	43	19	30	50	328
1993	26	16	72	28	17	50	12	45	22	32	62	382
1994	27	18	81	30	21	53	13	45	27	36	70	421
1995	29	19	95	35	23	74	14	48	29	38	77	481
1996	34	19	100	39	23	89	18	52	37	48	93	552
1997	36	21	107	46	24	99	18	57	38	48	112	606
1998	35	21	108	42	25	113	18	57	44	55	117	635
1999	38	21	109	51	26	129	23	59	47	59	127	689
2000	36	21	108	58	27	139	22	63	44	66	122	706
2001	43	20	111	64	25	114	25	64	47	67	122	702
2002	46	21	114	66	28	133	31	65	52	72	150	778
2003	49	24	125	71	29	173	38	66	57	82	158	872
2004	50	25	136	73	31	182	40	68	71	85	177	938
2005	51	29	142	86	33	202	47	72	79	84	196	1021
2006	54	30	158	99	39	214	50	76	84	94	226	1124
2007	57	35	164	108	39	230	54	79	88	100	238	1192
2008	57	25	151	98	34	183	47	85	85	101	230	1096
2009	63	34	175	109	42	235	50	89	93	115	255	1260
2010	69	39	194	123	45	280	53	90	101	123	280	1397
2011	70	46	186	145	48	284	62	90	104	123	292	1450
2012	73	43	192	144	52	304	63	93	113	126	304	1507
2013	79	46	205	152	54	330	69	94	141	138	344	1652
2014	85	48	197	121	60	350	71	107	141	159	357	1696
Total	1246	690	3312	1895	838	4177	876	1800	1630	1982	4391	22,837
%	5.46	3.02	14.5	8.3	3.67	18.29	3.84	7.88	7.14	8.68	19.23	100