Where is the risk in value? Evidence from a market-to-book decomposition

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Abstract

We study the value premium using a multiples-based market-to-book decomposition of Rhodes-Kropf, Robinson and Viswanathan (2005). The market-to-value component drives *all* of the value strategy return, while the value-to-book component exhibits no return predictability in either portfolio sorts or firm-level return regressions. Existing results linking market-to-book to long-run consumption risk, cashflow risk, exposure to investment-specific technology shocks, operating leverage, duration, and analysts' risk ratings derive predominantly from the unpriced value-to-book component. In contrast, results on expectation errors and limits to arbitrage emanate from the market-to-value component. Overall, our evidence casts doubt on most existing risk-based explanations for the value premium.

JEL classification: G12; G14

Keywords: Value Premium, Market-to-Book Decomposition, Risk Exposures, Expectation Errors, Limits to Arbitrage

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I. Introduction

The positive return differential between high book-to-market (value) and low book-to-market (glamour) stocks is one of the most pervasive phenomena in the behavior of stock prices, having been documented in many markets around the world (e.g., Fama and French (1998), Fama and French (2012), Asness, Moskowitz, and Pedersen (2013)). Despite such attention and prominence, there is no unanimity in the explanations for this book-to-market effect (also known as the "value premium"). The value premium could represent either compensation for risk embedded in value stocks, or some form of mispricing along the value/growth dimension.[1] Both explanations have found empirical support. For instance, Barberis, Shleifer, and Vishny (1998) and Daniel, Hirshleifer, and Subrahmanyam (2001) propose behavioral theories based on investor irrationality, whereas Zhang (2005), Lettau and Wachter (2007), and Kogan and Papanikolaou (2014) propose risk-based explanations based on costly investment reversibility, duration, and exposure to investment-specific technology shocks respectively.

The abundance of the proposed explanations for the value premium is perplexing. As pointed out by Lewellen, Nagel, and Shanken (2010), a great variety of asset pricing models seems to explain the cross-section of returns on book-to-market sorted portfolios, while having little in common in terms of underlying economic mechanisms. In this paper we show that a number of prominent risk-based explanations are actually at odds with the data, and the few stories that withstand our tests face other challenges. We dissect competing explanations using a market-to-book decomposition introduced by Rhodes–Kropf, Robinson, and Viswanathan (2005) in their study of merger waves (RRV hereafter). In particular, we decompose market-to-book into market-to-*value* and *value*-to-book components, where *value* is an estimate of fundamental value based on industry valuations conditional on a set of observable characteristics. The market-to-value component represents stock price deviation from fundamental value (total error hereafter), and is further decomposed into stock price deviation from contemporaneous industry valuation (firm-

[1] A third possibility is that return predictability in general is an artefact of data snooping (e.g., Lo and MacKinlay (1990), Fama (1991, (1998), Conrad, Cooper, and Kaul (2003)). However, this is an unlikely explanation for the book-to-market effect, as it has been documented in several different time periods, asset classes, and markets (see, e.g., Barber and Lyon (1997), Fama and French (1998), Davis, Fama, and French (2000), Asness, Moskowitz, and Pedersen (2013)). Further, Harvey, Liu, and Zhu (2016) show that the *t*-statistic of the HML factor is comfortably above the critical *t*-value adjusted for publication bias (they recommend a cut-off value of 3).

specific error hereafter) and the deviation of contemporaneous industry valuation from its long-run average (sector error hereafter).[2]

Our baseline results show that the entire value premium is concentrated in the market-to-value component. Over the 1975-2013 period, a long-short portfolio strategy based on the conventionally used market-to-book ratio produces an average return of 0.75% per month in return-weighted (RW) portfolios and 0.59% in value-weighted (VW) portfolios. The same strategy based on market-to-value produces an average RW return of 0.75% (0.43% VW), while the return spread between low and high value-to-book portfolios is about 10 basis points per month and statistically insignificant regardless of the weighting. Further decomposition of market-to-value shows that return predictability is driven by firm-specific error, whereas sector error exhibits no significant association with future stock returns. The Sharpe ratio of the firm-specific error strategy is higher than that of the market-to-book in RW portfolios, and almost as high as that of market-to-book in VW portfolios.

Firm-level stock return regressions produce consistent results. The market-to-value component negatively predicts future stock returns, while the value-to-book component has no explanatory power in the cross-section. That is, the market-to-value component subsumes *all* of the value premium. These results persist after controlling for numerous other firm-level characteristics such as size, market beta (upside and downside), idiosyncratic volatility, illiquidity, prior 1-month and 11-month returns (momentum and reversal effects), investment, and profitability.

Conceptually, deviations of market value from our estimates of fundamental value can arise due to the following. First, industry-year multiples may fail to fully capture cross-sectional differences in risk, leading to biased estimates of fundamental value. In this case subsequent returns represent compensation for an unmodelled risk factor.[3] Second, deviations can be due to relative over-/undervaluation, suggesting that subsequent returns represent corrections of prices towards fundamental value. The latter would also require mechanisms by which stock prices

[2] We recognize that any estimate of *value* likely deviates from “true” fundamental value. We therefore use the term “error” loosely.

[3] To illustrate this point, assume that we attempt to value a firm that is riskier than its industry-year peers. In this case, we would be using valuation multiples that are too high (discount rates that are too low), resulting in an inflated estimate of fundamental value. This, in turn, leads to lower values of the market-to-value component. Consequently, our findings of higher returns of low market-to-value stocks would be consistent with risk-based pricing.

become and remain dislocated for a prolonged period of time (De Long et al. (1990), Shleifer and Vishny (1997)).

We first explore the risk-based explanations. Literature shows that value premium represents compensation for cash flow risk (Campbell and Vuolteenaho (2004), Da and Warachka (2009)). If this is the case, we should find that cash flow risk exposures relate inversely to market-to-value – the component of market-to-book that exhibits predictability. We capture these exposures using three alternative approaches and show that the value strategy is indeed exposed to cash flow risk. However, two of our approaches, performed in the spirit of Da and Warachka (2009), suggest that this result is coming from value-to-book – the part of market-to-book that does not exhibit predictability. Only when we use the VAR-based return decomposition approach of Campbell and Vuoltenaaho (2004) to extract cash flow news, we find that market to value is inversely associated with cash flow betas, consistent with market to value being risky.[4] Under the same approach however, value to book exhibits a similar association with cash flow risk, despite the fact that value to book does not predict returns. Collectively, the evidence on cash flow risk as an explanation for the value premium is weak.

We further examine long-run consumption risk as an explanation for the value premium. Parker and Julliard (2005) show that ultimate consumption risk, measured as the covariance between asset returns and future consumption growth, explains largely the variation in returns across book-to-market portfolios. Bansal, Dittmar, and Lundblad (2005) further show that covariances between cash flow growth rates and past consumption growth are also successful in explaining the value premium. We replicate both studies and show that the association between market-to-book and *ultimate* consumption risk is mainly driven by market-to-value – the component of market-to-book that predicts returns. While this result suggests that market-to-value picks up consumption risk, this inference is not supported when exposures rely on cash flow growth rates and past consumption. In order to reconcile our conflicting findings, we re-estimate ultimate consumption risk exposures after replacing stock returns with three alternative proxies for cash flow news. Our results show no differential cash flow risk exposure across market-to-value portfolios, whereas there is some evidence of consumption risk being picked up by value-to-book.

[4] Chen and Zhao (2009) point out that reasonable variations in the set of state variables in the VAR return decomposition model can reverse the beta spread of value and growth stocks. We do not take a stance on this debate. However, our decomposition shows that the cash flow beta estimated exactly as in Campbell and Vuolteenaho (2004) would have a difficult time pricing market-to-value and value-to-book portfolios at the same time.

Overall, our results suggest that consumption risk embedded in cash flows cannot explain the differential risk premia across market-to-value portfolios. Therefore, postulating ultimate consumption risk as an explanation for the value premium relies on using returns in measuring exposures to consumption.[5]

Recent evidence also suggests that the value effect captures exposure to investment-specific technology shocks. Kogan and Papanikolaou (2014) find that growth stocks are more sensitive to changes in the prices of investment goods compared to value stocks, and this exposure earns a negative risk premium. Technological shocks tend to lower the cost of investment goods and value stocks miss out on those benefits. We find that the value strategy does capture exposure to investment-specific technology shocks, but once again this is largely due to the value-to-book component. Therefore, exposure to investment-specific technology is an unlikely explanation for the value premium.

We further explore operating leverage – a focal feature of production-based models giving rise to cash flow risk and the value premium (Carlson, Fisher, and Giammarino (2004), Zhang (2005), Novy-Marx (2011)). Operating leverage, in the form of fixed costs of production, makes assets-in-place riskier than growth options, and market-to-book is commonly believed to be a proxy for the mix of assets-in-place versus growth options. However, using several common proxies for assets-in-place/growth-option intensity, we show that differences in the mix of assets-in-place versus growth options across market-to-book portfolios are due to value-to-book. There are no differences in assets-in-place intensity across market-to-value portfolios. Therefore, even if operating leverage is a priced source of risk, it is unlikely to be the mechanism behind the value premium.

Another risk-based explanation for the value premium is based on cash flow duration (Lettau and Wachter (2007)). Several studies show empirically that value stocks have shorter cash flow durations than growth stocks (Dechow, Sloan, and Soliman (2004), Da (2009), Chen (2017)). Once again we show that differences in cash flow duration are due to the unpriced value-to-book

[5] The use of cash flows to measure exposure to potential risk factors in the original studies was partly motivated by the possibility that resolution of mispricing (if any) can bias the measured covariances between realized returns and the risk factors, in favor of finding a beta spread between undervalued and overvalued assets (see Cohen, Polk, and Vuolteenaho (2009) for a formal argument). The idea that surprises affect realized returns and therefore the outcome of the associated asset pricing tests has also been pointed out by Elton (1999). Our subsequent tests show that market-to-value is associated with surprises both pre- and post- portfolio formation.

component. That is, duration cannot explain the value premium. Finally, in the accounting literature, Lui, Markov, and Tamayo (2007) show that equity analysts perceive value stocks to be riskier than growth stocks. While we confirm a negative association of analysts' risk ratings with market-to-book, this correlation is once again driven by the unpriced value-to-book component. We emphasize that we do not take a stance on whether the risk characteristics that we explore represent priced sources of risk – we only examine their ability to explain the value premium.[6]

In the final part of the paper we revisit the explanations that appeal to expectational errors and limits to arbitrage. Previous research suggests that prices of glamour (value) firms reflect overly optimistic (pessimistic) expectations, as captured by the market reaction to earnings announcements following portfolio formation. If the value premium is due to irrational expectations, we should find that these associations are driven by the market-to-value component. This is exactly what we find. Furthermore, for both market-to-book and market-to-value we find earnings surprises of the *opposite* sign in the quarters *prior* to portfolio formation. This latter result is new to the literature and is consistent with investors over-extrapolating news about fundamentals. The same patterns are not there for the unpriced value-to-book component.

Prior research also highlights that the value premium is coming largely from stocks characterized by limits to arbitrage, such as short sale constraints and noise trader risk – forces that can sustain deviations of stock prices from intrinsic value ((Nagel (2005), Ali, Hwang, and Trombley (2003), Pontiff (2006)). We find that these results are, indeed, due to the market-to-value component. Finally, we conduct a novel time-series test utilizing changes in the availability of arbitrage capital, which has been shown to improve stock market efficiency (Kokkonen and Suominen (2015)). Consistent with the value effect emanating from stock price dislocations, market-to-book and market-to-value strategies are profitable only when arbitrage capital at the time of portfolio formation is low.

We argue that, taken as a whole, our results challenge most risk-based explanations for the value premium. The exceptions are cash flow risk (bad beta) of Campbell and Vuolteenaho (2004) and ultimate consumption risk of Parker and Julliard (2005), although both hinge on the use of realized returns in measuring covariances. We recognize, however, that our tests of the risk-based

[6] Another popular risk-based explanation of the value premium appeals to distress risk (e.g., Fama and French (1992)). However, this explanation has found little empirical support, hence we do not re-examine this evidence. See Griffin and Lemmon (2002), Campbell, Hilscher, and Szilagyi (2008), and Da and Gao (2010).

explanations rely on properly estimating the relevant risk loadings. To the extent that our beta estimates can be noisy, rejection of the risk-based explanations should be viewed as rejection of the joint hypothesis of the model being true *and* the corresponding risk loadings being properly estimated. In light of this limitation, the additional results we document are helpful. Specifically, while we cannot rule out all potential risk-based stories or avoid the joint hypothesis problem, any risk explanation for the value premium would have to offer a very nuanced theory for why this risk is i) associated with negative earnings surprises prior to – and positive earnings surprises following – portfolio formation; and ii) concentrated in stocks and time periods characterized by limits to arbitrage.

Our paper is related to the work of Daniel and Titman (2006), Fama and French (2008), and Gerakos and Linnainmaa (2017) who use a returns-based book-to-market decomposition and show that it is the change in market value component that is largely responsible for return predictability. Our work is also related to Piotroski and So (2012) who show that the underperformance of growth stocks is concentrated among firms with ex-ante identifiable accounting-based characteristics suggestive of deteriorating fundamentals. Our market-to-book decomposition is novel to the asset pricing literature and is used to directly evaluate the validity of a number of risk-based and behavioral-based explanations for the value premium.

The rest of the paper is organized as follows. Section II discusses the market-to-book decomposition and related studies. Section III describes our data sources, sample composition, and variables construction. We present the main empirical results in Sections IV, V, and VI. Robustness checks are in Section VII. Finally, Section VIII concludes the paper.

II. RRV Market-to-Book Decomposition and Related Literature

The market-to-book decomposition that we use was introduced by RRV in their study of merger waves. Conceptually, the market-to-book ratio can be decomposed as follows:

$$\textit{Market-to-Book} = \textit{Market-to-Value} \times \textit{Value-to-Book} \tag{1}$$

where *Value* is an estimate of fundamental value. Using lower-case letters to denote values expressed in logs, the above is equivalent to:

$$m - b = (m - v) + (v - b) \tag{2}$$

The expression $(m - v)$ denotes stock price deviation from fundamental value, whereas $(v - b)$ is the difference between fundamental value and book value. If stock prices accurately reflect fundamentals, then $(m - v)$ equals zero and $(m - b)$ equals $(v - b)$. However, if for whatever reason stock price deviates from fundamental value, then $(m - v)$ does not equal zero.

RRV operationalize this decomposition using annual industry-level cross-sectional regressions of equity values on firm fundamentals. In this setup, the coefficients obtained from the annual industry-level regressions can be interpreted as time-varying valuation multiples that account for variation in investors' expectations of returns and growth over time and across different sectors. These multiples are then averaged across time to compute long-run fundamental equity values, v. This setup is particularly useful for the purpose of disentangling risk/growth opportunities theories from behavioral stories – to the extent that discount rates and growth opportunities vary by industry, within-industry estimation strips away such variation and the unexplained part of market value can be more readily interpreted as relative over-/undervaluation.

The time-varying nature of industry-level multiples allows further breaking down stock price deviations from fundamental value (total error) into stock price deviations from contemporaneous industry valuations (firm-specific error) and deviations of contemporaneous industry valuations from valuations implied by long-run industry multiples (sector error):

$$m_{it} - b_{it} = \underbrace{m_{it} - v(\theta_{it};\, \alpha_{jt})}_{\textit{firm-specific error}} + \underbrace{v(\theta_{it};\, \alpha_{jt}) - v(\theta_{it};\, \alpha_{j})}_{\textit{sector error}} + \underbrace{v(\theta_{it};\, \alpha_{j}) - b_{it},}_{\textit{long-run value-to-book}} \tag{3}$$

where subscrpipt i denotes firm, subscript t denotes time, and subscript j denotes industry.

Using this decomposition, RRV show that high market-to-value firms tend to be acquirers and tend to use their own stock as the method of payment when making acquisitions, while low market-to-value firms tend be to targets. They interpret these results as consistent with the stock market driven acquisitions theories of Shleifer and Vishny (2003) and Rhodes-Kropf and Viswanathan (2004) whereby overvalued firms exchange their overpriced equity for hard assets of relatively less overvalued or undervalued targets. The same decomposition has been used in subsequent studies in the mergers and acquisitions literature. Maksimovic, Phillips, and Yang (2013) show that public firms' participation in merger waves is more affected by market valuations than that of private firms. In addition, Fu, Lin, and Officer (2013) address value creation in such stock market driven acquisitions. They find that overvalued acquirers tend to offer higher premiums and exhibit inferior long-run stock price performance following acquisitions than less overvalued ones. The authors interpret these results as consistent with the agency costs of overvalued equity hypothesis of Jensen (2005).

Hertzel and Li (2010) also use this decomposition to study long-run stock underperformance following seasoned equity offerings (SEO). They find that issuing firms have both higher market-to-value and value-to-book components. Interpreting the former as overvaluation and the latter as long-run growth opportunities, they argue that SEO issues are motivated by both overvaluation and capital needs. In line with this explanation, they show that high value-to-book firms tend to invest proceeds in capital expenditure and research and development and do *not* experience long-run underperformance, whereas high market-to-value firms hoard proceeds as cash or pay down debt and exhibit negative abnormal post-issue stock returns.

To the best of our knowledge, we are the first to introduce this market-to-book decomposition to the asset pricing literature.

III. Sample and Data

Our main data source is the intersection of CRSP and Compustat databases over the period 1970-2013, although all our main tests start from 1975 as we require 5 years of prior data for the market-to-book decomposition. The estimation sample for the decomposition starts in 1970 and not earlier to allow for a sufficient number of firms (minimum of 30) to enter the industry-level cross-sectional regressions required for the market-to-book decomposition. For the same reason, we use the 12 Fama-French industry classifications for our valuation models: finer industry definitions cause several industries to have fewer than 30 firms per year. Nevertheless, in the robustness checks section we experiment with alternative industry classifications, including Fama-French 30 and 38, as well as the Campbell (1996) 12 industry definitions and find consistent results.

We keep only common stocks (CRSP share codes 10 and 11) listed on NYSE, Amex, or Nasdaq (CRSP exchange codes 1, 2 and 3). We exclude firm-year observations with SIC codes in the range 6000–6999 (financial firms) because the behavior of earnings and other financial statement numbers for these firms is different. Following RRV, we exclude stocks with market values of equity below $10 million. Finally, we eliminate outliers or potential data errors in the variables entering the valuation model by requiring market-to-book ratios to lie between 0.01 and

100, return on equity to fall between -1 and 1, and leverage to be between 0 and 1. Table 1 presents details of sample construction (Panel A), industry composition using the 12 Fama-French industry classification excluding financials (Panel B), and descriptive statistics of the variables entering the decomposition analysis (Panel C)

[Please Insert Table 1 about Here]

In later analysis we supplement the main dataset with additional variables from Thomson Reuters 13f Holdings (institutional ownership), I/B/E/S (earnings forecasts), HFR and Lipper (arbitrage capital availability) and a proprietary dataset of monthly equity risk ratings reported by financial analysts in a large securities firm. Consumption data are obtained from the Bureau of Economic Analysis of the U.S. Department of Commerce. Detailed definitions of all variables are provided in Appendix A.

Table 2 presents the time-series average coefficient estimates of the valuation model estimated every year for each of the 12 Fama-French industries (excluding financials). We use the most comprehensive specification of the valuation model from RRV:

$$m_{it} = \alpha_{0jt} + \alpha_{1jt}b_{it} + \alpha_{2jt}ni^{+}_{it} + \alpha_{3jt}I_{(<0)}(ni^{+}_{it}) + \alpha_{4jt}LEV_{it} + \varepsilon_{t}, \tag{4}$$

where m_{it} is the log of market value of equity, b_{it} is the log of book value of common equity, ni^{+} is the log of the absolute value of net income, LEV_{it} is book leverage, and ε_t is an error term. An indicator variable $I_{(<0)}$ is interacted with the log of absolute net income (ni^{+}) to separately estimate the earnings multiple for firms with negative net income.

To eliminate look-ahead bias, the valuation model is estimated always as of June 30 of each year (i.e. all market values are as of June 30) and we require a 3 months' lag at a minimum for the accounting information to become publicly available (Hou, van Dijk, and Zhang (2012), Li and Mohanram (2014)). Therefore, to estimate the valuation model in June of year *t*, we only use the financials of firms with fiscal year-end from April of year *t*-1 until March of year *t*. For example, if 2000 is year *t*, we use data from April 1999 until March 2000 to estimate the industry-year valuation multiples as of June 2000. To estimate the long-run industry valuation multiples, we adapt the RRV approach to the asset pricing setting and compute time-series averages of industry-year multiples over the *past* 5 years including the current year (as opposed to the whole sample in RRV). For example, if 2000 is year *t*, we use averages of valuation multiples over the period from June 1996 to June 2000 to compute long-run intrinsic values as of June 2000. As a result, the first portfolio formation date is June 1975 and the last one is June 2012; return tracking ends in June 2013 which allows for tests requiring forward-looking fundamentals (consumption and earnings) to be conducted on a constant sample. In consistency with our fundamental value estimation, market-to-book is defined as market value of equity on June 30 of each year divided by the book value of equity that goes into the valuation model.

The R^2s reported in Table 2 indicate that our valuation model explains between 80-95% of the variation in market values. The book value of equity (α_1) and net income (α_2, $\alpha_2 + \alpha_3$) are consistently relevant in explaining market value across all industries, while leverage (α_4) is incrementally relevant for nine out of eleven industries. The incremental coefficient on negative net income realizations is negative, consistent with the transitory nature of negative earnings. Panel B of Table 2 reports the descriptive statistics on the output of the decomposition model.

In the two-part decomposition, ln(M/B) ($m_{it} - b_{it}$) is decomposed into i) total error ($m_{it} - v(\theta_{it}; \alpha_j)$) and ii) long-run value-to-book ($v(\theta_{it}; \alpha_j) - b_{it}$), where $v(\theta_{it}; \alpha_j)$ is the predicted value of m from equation (4) using coefficient estimates averaged over the last 5 years. The valuation model produces a mean total error component of 0.021 with a standard deviation of 0.698, and a mean value-to-book of 0.583 with a standard deviation of 0.532; both components exhibit meaningful variation. By construction, the two means add up to the mean of ln(M/B) of 0.604, with a standard deviation of 0.856. The three-part decomposition further decomposes the total error component into firm-specific error ($m_{it} - v(\theta_{it}; \alpha_{jt})$) and sector error ($v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$). Here, $v(\theta_{it}; \alpha_{jt})$ is the fitted value from equation (4). Firm-specific error exhibits greater variation than sector error, and has a mean value of zero by construction, as it is the OLS residual from (4).

[Please Insert Table 2 about Here]

IV. Return Predictability Tests

IV.A Portfolio Sorts

We begin our analysis with the usual portfolio sort tests for the market-to-book and its components. Consistent with earlier studies, we use NYSE breakpoints to form our portfolios. We rebalance those annually in July when the valuation model is re-estimated. Following Asparouhova, Bessembinder, and Kalcheva (2013), we use prior-period gross return weighted (RW) and value-weighted (VW) portfolio returns. Both weighting schemes address return measurement biases in equal-weighted portfolios arising from microstructure noise. Since value-weighting deprioritizes small stocks where the value premium is known to be larger, we use both types of portfolios.[7] We also examine sorts on market-to-book and its components *within* size quintiles. When a firm delists, we use the delisting return in the delisting month. If a delisting is due to liquidation (delisting codes 500 or between 520 and 584) and the delisting return is missing, the delisting return is set to -30% for NYSE/AMEX firms (Shumway (1997)) and -55% for NASDAQ firms (Shumway and Warther (1999)). Table 3 presents the results.

Panel A reports average monthly returns of 10 RW portfolios sorted on market-to-book or its components over the 12 months after portfolio formation. There is a monotonic decline in returns moving from low to high market-to-book decile. The long-short strategy generates a return of 0.754% per month, highly statistically significant. The annualized Sharpe ratio of this strategy is 0.594. This pattern is mimicked by the total error component which produces the same mean return of 0.754% per month but with lower volatility, resulting in a Sharpe ratio of 0.709. Firm-specific error increases the mean hedge portfolio return to 0.852% per month and reduces further volatility, resulting in a Sharpe ratio of 0.901. Portfolio strategies based on sector error or value-to-book result in a hedge return of about 0.12% per month, both statistically insignificant. Panel B reports the same tests using VW portfolio returns. The first column reveals the familiar value premium of 0.588% per month with a Sharpe ratio of 0.450. Once again, this pattern is driven by the market-to-value components. The second column uses the total error component as the sorting variable and shows a somewhat lower long-short return of 0.433% per month; the volatility is also reduced resulting in a Sharpe ratio of 0.359. The firm-specific error strategy produces a similar hedge return of 0.411% but further reduces volatility leading to a Sharpe ratio of 0.390, comparable to that of the conventional market-to-book. The last two columns repeat the sorts using sector error and value-to-book and reveal economically and statistically insignificant long-short strategy returns.

Figure 1 plots the cumulative performance of market-to-book, total error, firm-specific error, sector error and value-to-book strategies over the sample period. Panel A illustrates the RW strategies. It is evident that firm-specific error is solely responsible for the performance of the

[7] For example, the widely used HML factor overweighs small stocks as it is constructed as an *equal*-weighted average of HML Small and HML Big, where HML Small and HML Big are value-weighted returns of value-minus-growth strategies implemented among small and big stocks respectively. See Professor Kenneth French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/Data_Library/f-f_factors.html

market-to-book strategy. In fact, this strategy achieves a slightly higher terminal wealth with lower volatility: the firm-specific error largely avoids the well-known crash of the value strategy during the dotcom period and significantly reduces the drawdown in 1980. The sector error strategy and the value-to-book strategy exhibit little in the form of wealth accumulation but do show relatively high volatility. Panel B shows the performance of the VW strategies. Here again, the performance of the firm-specific error strategy largely mimics that of market-to-book until the year 2002, although overall it results in a slightly lower terminal wealth than the market-to-book strategy. Sector error and value-to-book are volatile and result in no wealth accumulation.

We further examine sorts on market-to-book and its components within size quintiles. For brevity, these results are reported in Tables A1-A2 of the Internet Appendix. Consistent with the literature, the value premium is larger in small stocks. The pattern of return predictability of total error and firm-specific error across size quintiles follows that of market-to-book. Moreover, it is statistically significant in all but the largest size quintile using RW portfolios, and in all but the two largest quintiles using VW portfolios. Sector error and value-to-book do not exhibit return predictability in any size quintile.

Finally, we also experiment with estimating the valuation model (equation (4)) using per share values (scaling the market value of equity, book value of equity, and net income variables by the number of shares outstanding). The R^2s of these alternative specifications range between 57% and 73% depending on the industry. We continue to find that the return predictability of market-to-book is driven by firm-specific error and the magnitudes of the hedge returns are similar to those in our baseline results from the decomposition model estimated in levels (see Table A12 in the Internet Appendix).

Overall, the results in this section show that all of the return predictability of the market-to-book ratio comes from the market-to-value component, i.e. stocks whose market value is low relative to estimated fundamental value exhibit high returns, and vice versa. Sorting on the value-to-book component that isolates deviations of book value from expected long-run value generates no excess returns. In the next section we study whether these patterns continue to hold after considering other firm-level determinants of stock returns.

[Please Insert Table 3 and Figure 1 about Here]

IV.B Firm-level Return Regressions

We perform Fama-MacBeth regressions of monthly individual stock returns on the market-to-book ratio or its components, and a set of other stock characteristics known to predict stock returns. The typical OLS estimation of the Fama-MacBeth regressions found in the literature implies equal weighting of stocks within a period. Asparouhova, Bessembinder, and Kalcheva (2010) show that slope coefficients in these regressions can be biased in the presence of microstructure noise and recommend weighting the estimation by prior period gross return (RW), which is what we report in Table 4.[8]

Column (1) estimates a basic firm-level return regression on the conventional market-to-book ratio, producing the familiar negative association. In Column (2) we replace the market-to-book ratio with the components from the basic decomposition: total error and value-to-book. Consistent with the portfolio sort results, we find that total error has a strong negative association with subsequent stock returns, while value-to-book obtains a statistically insignificant coefficient. In Column (3) we further decompose total error into firm-specific error and sector error. We find that firm-specific error has a strong negative association with subsequent stock returns, sector error obtains a negative coefficient but not statistically significant and value-to-book has a coefficient close to zero.

Columns (3), (4), and (5) repeat the previous specifications but this time controlling for additional firm-level characteristics, namely, market value (*Size*), upside and downside beta (β^{+} and β^{-}), idiosyncratic return volatility (*IVol*), illiquidity (*Illiquidity*), momentum (Ret^{-2-12}), reversal (Ret^{-1}), operating profitability (*OP*), and investment (*Inv*). The inclusion of these characteristics does not change the results on the main variables of interest. The conventional market-to-book effect in Column (4) continues to hold, and the decomposition results in Columns (5) and (6) continue to indicate that it is the firm-specific error component that drives return predictability of the market-to-book ratio. The newly added characteristics obtain signs consistent with existing literature: large stock have lower returns (Banz (1981)), high downside beta stocks have higher returns (Ang, Chen, and Xing (2006)), high idiosyncratic volatility stocks have lower returns (Ang et al. (2006)), more illiquid stocks have higher returns (Amihud (2002)), high past month returns

[8] None of our inferences change if we employ the commonly used equal-weighted Fama-MacBeth regressions. Value-weighted Fama-MacBeth regressions do not appear to be standard in the literature; nevertheless, we perform them for completeness and find consistent results (reported in Table A3 of the Internet Appendix).

stocks have lower returns (Jegadeesh (1990)) while high past year returns stock have higher returns (Jegadeesh and Titman (1993)), higher profitability is associated with higher stock returns (Novy-Marx (2013), Ball et al. (2015)), and higher asset growth is associated with lower returns (Titman, Wei, and Xie (2004), Cooper, Gulen, and Schill (2008)).

[Please Insert Table 4 about Here]

Overall, our evidence thus far indicates that stocks whose market values are above (below) our estimated fundamental values exhibit relatively low (high) subsequent stock returns. What can this pattern represent? First, it is possible that the industry-year multiples in our valuation model do not fully capture cross-sectional differences in risk, and thus lead to incorrect estimates of v. Under this scenario, variation in the market-to-value components captures risk and the return predictability of market-to-value represents a risk premium.[9] Alternatively, deviations from estimated fundamental value can reflect relative over-/undervaluation, in which case subsequent returns represent corrections towards fundamental value. The latter possibility also requires a mechanism by which stocks move away from fundamental value (e.g., some form of investor irrationality) and forces that sustain such dislocations for a prolonged period of time. We now address these two possibilities through the lens of our decomposition.

V. Risk-Based Explanations

V.A Cash flow Risk

If existing risk-based stories explain the value/growth effect, we should find that they also explain the market-to-value effect, since this is the component of market-to-book that exhibits return predictability. Campbell and Vuolteenaho (2004) argue that the value premium can be explained by greater sensitivity of value stocks' returns to market-level cash flow shocks, which they estimate using a vector autoregression (VAR) decomposition of the market return. Da and Warachka (2009) provide further evidence that value stocks' cash flows news, as measured by revisions in analysts' earnings forecasts, are more sensitive to market-level cash flow news compared to growth stocks. We explore the cash flow risk explanation for the value premium using

[9] To illustrate this point, assume that we attempt to value a firm that is riskier than its industry-year peers. We would be applying valuation multiples that are too high (discount rates that are too low) for this firm, resulting in a fundamental value estimate (v) that is higher than its true value. Higher estimates of v lead to lower values of market-to-value ($m – v$). Therefore, the higher returns of low $m – v$ stocks could represent compensation for greater risk that is not properly accounted for by the industry-year multiples.

our decomposition. The results are reported in Table 5. To conserve space, from this point forward we present results using RW portfolio returns (risk factor returns on the right hand-side are always value-weighted). None of our inferences change when we use VW portfolios and we always point out any sizable quantitative differences. VW results can be found in the Internet Appendix.

Using the exact VAR specification as in Campbell and Vuolteenaho (2004) we confirm that value stocks' returns are more sensitive to market-level cash flow shocks compared to growth stocks (Table 5 Panel A). The cash flow beta spread between value and growth stocks is 0.153 and significant at the 1% level. Turning to the components, we find that both total error and firm-specific error exhibit a statistically significant cash flow beta spread, although somewhat smaller in magnitude (0.123 and 0.117, respectively). The cash flow beta spread across sector error portfolios is small and statistically insignificant. Interestingly, value-to-book exhibits a significant cash flow beta spread of almost the same magnitude (0.085) as firm-specific error, although value-to-book does not predict returns. VW portfolio results, which are reported in the Internet Appendix (Table A4), yield same inferences. Overall, while we confirm that market-to-book captures variation in cash flow risk, we find that such cash flow risk is associated with the priced but also the unpriced component of market-to-book.

Chen and Zhao (2009) revisit the Campbell and Vuolteenaho (2004) return decomposition approach and find it to be sensitive to the state variables included in the VAR model. This is because market-level cash flow news is estimated residually rather than directly, such that any expected return model misspecification affects the resulting cash flow news estimates. Evidence by Chen and Zhao (2009) shows that reasonable variations to the set of state variables results in the reversal of the beta spread between value and growth stocks. Da and Warachka (2009) address this shortcoming by exploiting cash flow expectations provided by analysts, which allows computing cash flow news without a model of expected returns. Specifically, Da and Warachka (2009) define cash flow news as revisions in the discounted sum of analysts' earnings forecasts, and measure the sensitivity of portfolio-level cash flow news to those of the market portfolio. They find that such beta is monotonically related to book-to-market, suggesting that the value premium can be, indeed, due to cash flow risk.

We follow Da and Warachka (2009) and compute cash flow betas for our market-to-book portfolios, and for portfolios formed based on our components. Analysts' earnings forecasts data are from I/B/E/S. The sample size in these tests declines naturally given that not all stocks appear in I/B/E/S. Panel B of Table 5 reports the results of these tests.[10] Column (1) shows cash flow betas for the conventional market-to-book portfolios. Consistent with Da and Warachka (2009), the cash flow betas of these portfolios are monotonically decreasing with the market-to-book ratio. The difference in the betas between the extreme deciles is 0.242 and highly statistically significant. The cash flow betas of extreme portfolios based on total error, firm-specific error and sector error exhibit no statistically significant differences. In fact, all of the difference in cash flow beta spread across market-to-book portfolios is coming from value-to-book. That is, while the value strategy loads on cash flow risk, the component of the value strategy that is responsible for the return premium does not.

Finally, as a robustness check on the Da and Warachka (2009) approach, we replace revisions in the discounted sum of analyst earnings forecasts with changes in the discounted sum of future annual earnings realizations (ROEs) over a 5-year horizon (see, e.g., Vuolteenaho (2002)). Results reported in Panel C of Table 5 show that market-to-book portfolios exhibit a positive but insignificant beta spread, which is once again driven by the significant beta spread between the extreme value-to-book portfolios. Total error and firm-specific error exhibit beta spreads of the wrong sign (low *m–v* firms have lower cash flow betas than high *m–v* stocks) and sector error shows no particular pattern.

Overall, only when we use the VAR-based return decomposition approach of Campbell and Vuoltenaaho (2004) to extract cash flow news, we find that market-to-value is inversely associated with cash flow betas, consistent with market-to-value being risky. Under the same approach however, unpriced value-to-book appears almost as risky, meaning that such cash flow beta would have a difficult time pricing both market-to-value and value-to-book portfolios at the same time (in the spirit of "Prescription 1" in Lewellen, Nagel, and Shanken 2010)). Cash flow-based approaches designed to address some of the limitations of the VAR-based return decomposition approach reject the cash flow risk explanation of the value premium when confronted with our decomposition.

[Please Insert Table 5 about Here]

[10] Da and Warachka (2009) deflate earnings and book values with price prior to aggregating them within portfolios. We intentionally skip this step in order to exclude price from the construction of the measure – to avoid mispricing effects (if any) affecting the results. Our inferences remain exactly the same if we do not make this change. Also, as fundamentals (earnings and book values) are aggregated within portfolios, there is no distinction between RW and VW tests.

V.B Long-Run Consumption Risk

We further examine long-run consumption risk as an explanation for the value premium. Parker and Julliard (2005) show that ultimate consumption risk, measured as the covariance between asset returns and consumption growth *over the subsequent three years*, explains largely the variation in returns across book-to-market portfolios. Bansal, Dittmar and Lundblad (2005) further show that consumption risk, measured as the covariance between cash flows and consumption growth *over the past two years*, is also successful in explaining the value premium.

Table 6 presents the sensitivities of portfolio returns to ultimate consumption growth. Following Parker and Julliard (2005), quarterly portfolio returns (obtained by cumulating monthly returns within a quarter) are regressed on the log growth rate in real per capita consumption of non-durable goods from quarter t to quarter t+11. The results confirm that value stocks have indeed higher sensitivity to ultimate consumption growth than growth stocks, and the beta spread is large (0.694) and statistically significant. Turning to the components, both total error and firm-specific error exhibit significant beta spreads, albeit somewhat smaller in magnitude (0.557 and 0.532, respectively). Value-to-book also has a marginally significant beta spread, while sector error does not show any pattern in ultimate consumption beta. Results using VW portfolios (Table A5 of the Internet Appendix) are somewhat different in that the beta spreads in total error and firm-specific error miss the conventional significance levels, sector error now behaves similarly to total error, and the beta spread in value-to-book is reduced and is no longer significant. Despite a more mixed picture from VW portfolios, on balance there is some evidence that firm-specific error strategy loads on ultimate consumption growth.

We now turn to the Bansal, Dittmar and Lundblad (2005) evidence and estimate the sensitivity of portfolio-level cash flows to average consumption growth over the last 2 years (γ from equation (7) and Table III of Bansal, Dittmar and Lundblad (2005)). Specifically, we regress, at the quarterly frequency, the seasonally-adjusted (4-quarter moving average) log growth rates in portfolio dividends on smoothed (8-quarter moving average) log growth rate in real per capita consumption of non-durables plus services. The results are reported in Panel B of Table 6. We find no evidence that dividends of value stocks are more sensitive to consumption growth in our sample period. The beta spread between value and growth stocks is close to zero. The same is true for all of the components of market-to-book. While the beta spreads are positive for total error and firm-specific error, they are far from the conventional significance levels. Inferences from tests using

VW portfolios (Table A3 of Internet Appendix) are the same. Neither market-to-book nor firm-specific error exhibit statistically significant beta spreads. Thus, the cash flows of value stocks, as measured by the dividend streams of managed portfolios, are not more sensitive to past consumption growth compared to growth stocks.[11]

So far, the results indicate that the returns of low market-to-book and low market-to-value portfolios are sensitive to consumption growth, while the associated cash flows are not. Of course, the two approaches differ both in terms of the outcome variable (realized returns vs. dividends) and in terms of the measure of consumption growth (future vs. past).[12] In order to reconcile the two sets of results, we estimate the sensitivity of portfolio dividends as in Bansal, Dittmar and Lundblad (2005) to ultimate consumption growth of Parker and Julliard (2005). Panel C of Table 6 presents the results. We continue to find no beta spread across value and growth portfolios when using ultimate consumption growth on the right-hand side. Therefore, the use of portfolio returns appears important. To further investigate this issue, we employ two additional measures of portfolio cash flows, which are used also in the section on cash flow risk. The first one is the Da and Warachka (2009) cash flow news measure based on revisions in analysts' earnings forecasts. We aggregate the monthly revisions to quarterly by adding up the monthly cash flow news within a quarter, in order to match the frequency of the consumption growth series. The second approach defines cash flow news as changes in the sum of discounted future ROEs over a 5-year horizon, which are regressed on ultimate consumption growth as of quarter 4.

The results reported in Panels D and E of Table 6 indicate that neither of these measures of portfolio cash flows reveals differential sensitivity of market-to-book or firm-specific error portfolios to ultimate consumption. Using the Da and Warachka (2009) analysts' earnings forecasts measure (Panel D), we find that the cash flows of the conventional value strategy covary positively with ultimate consumption growth, although the beta spread is not statistically significant at conventional levels. This effect appears to be coming from value-to-book, where the beta spread is significant, albeit not monotonic. Other components do not show significant beta

[11] Our sample period and sample formation criteria are different from those of Bansal, Dittmar and Lundblad (2005). When we estimate the sensitivities of market-to-book portfolios on the same sample, we are able to replicate the pattern of betas and the beta spread of almost exactly the same magnitude as in the original paper. However, this beta spread is not statistically significant. Bansal, Dittmar and Lundblad (2005) do not report their standard errors.

[12] Another difference between the two approaches is that Parker and Julliard (2005) use consumption of non-durable goods only, whereas Bansal, Dittmar, and Lundblad (2005) use consumption of non-durables plus services. We verified that this causes only a minor difference in the results.

spreads. Using the changes in future earnings realizations (Panel E) paints a similar picture. Market-to-book exhibits a positive beta spread, albeit statistically insignificant, and it appears to be driven by the value-to-book component. The total error, firm-specific error, and sector error exhibit negative beta spreads with respect to ultimate consumption growth.

Overall, the returns of low market-to-book and low firm-specific error stocks are more sensitive to future consumption growth, but their cash flows are not. Thus, the explanation of the value premium based on long-run consumption risk hinges on the use of realized returns to measure exposures.

[Please Insert Table 6 about Here]

V.C Investment-Specific Technology Shocks

Kogan and Papanikolaou (2014) argue that firms with higher market-to-book ratios earn lower returns because they are more exposed to positive investment-specific technology (IST) shocks (declines in quality-adjusted prices of investment goods) that carry a negative risk premium. In their model, firms with a higher fraction of growth opportunities (as opposed to assets in place) in their market value (growth firms) need to invest more in order to realize this growth. Therefore when a positive IST shock hits, growth firms benefit more, giving rise to differences in risk premia across value and growth stocks. Empirically, the exposure to IST shocks is captured by the covariance between asset returns and the returns on a factor mimicking portfolio going long investment goods producers and short consumer goods producers (IMC). Kogan and Papanikolaou (2014) show that portfolios formed on the basis of IMC beta exhibit a return spread (i.e. exposure to investment-specific technology shocks is priced) as well as a monotonic relation with the HML beta.

We examine the IST exposure explanation for the value premium through the lens of our market-to-book decomposition. We measure IMC betas for our market-to-book portfolios, as well as for portfolios formed on the basis of our decomposition. Table 7 presents the results. Consistent with the results in Kogan and Papanikolaou (2014), we find that market-to-book portfolios exhibit a monotonic pattern in their exposure to IST shocks – value firms are less exposed and growth firms are more exposed. The difference between the extreme portfolios' exposures is -0.269 and highly statistically significant. The total error sort reveals an IMC beta spread that is half the size (-0.140), and the firm-specific error sort exhibits an IMC beta spread that is only a third (-0.095) of the spread in market-to-book portfolios. Both are only marginally statistically significant. At the same time, the beta spread between extreme value-to-book portfolios is even more pronounced (-0.452) than that in market-to-book and highly statistically significant. The sector error sort reveals no pattern in the IMC beta.

Overall, the results suggest that the IMC beta spread in market-to-book is largely driven by the value-to-book component. Results based on VW portfolios (Table A6 of the Internet Appendix) are even less supportive of the idea that the value premium is compensation for exposure to IST shocks. The IMC beta spread across market-to-book portfolios is negative as predicted, but not statistically significant.[13] Total error and firm-specific error exhibit beta spreads of the opposite sign to that predicted by the theory. Interestingly, value-to-book continues to exhibit a statistically significant negative IMC beta spread. Yet, value-to-book is not priced in the cross-section in either RW or VW portfolios. Hence, differential exposure to investment-specific technology shocks cannot be responsible for the value premium. Again, this is not to say that exposure to such shocks is not a priced risk factor – it is just that it is not the reason behind the market-to-book effect.

[Please Insert Table 7 about Here]

V.D Operating Leverage

Several prominent production-based models generate the value premium via an operating inflexibility/operating leverage channel (Carlson, Fisher, and Giammarino (2004), Zhang (2005), Novy-Marx (2011)). Specifically, when capital is costly to adjust, operating inflexibility in the form of fixed costs of production makes less efficient (low Q or market-to-book) producers more exposed to economic downturns. Zhang (2005, p. 68) writes: "In bad times, value firms are burdened with more unproductive capital, finding it more difficult to reduce their capital stocks than growth firms do. The dividends and returns of value stocks will hence covary more with economic downturns."[14] More generally, operating inflexibility can make assets-in-place riskier than growth options.

[13] Note that Kogan and Papanikolau (2014) report equal-weighted averages of HML betas across IMC beta-sorted portfolios. Hence, their results are more directly comparable to our RW portfolios.

[14] Note however, that the market-to-book and market-to-value effects survive controls for downside beta in our firm-level return regressions in Table 4, casting doubt on this type of risk as the mechanism behind the value premium.

In both Novy-Marx (2011) and Zhang (2005) models, firm-level productivity is the only source of firm heterogeneity, and thus the only source of differences in market-to-book and expected returns. Novy-Marx (2011) relates capital productivity to an empirical measure of operating leverage (operating costs divided total assets) and argues that a return spread arises between high cost producers (value firms) and low cost producers (growth firms). However, although high operating leverage relates to higher returns, this does not detract from the market-to-book effect. Moreover, in Novy-Marx (2013), more profitable firms (efficient producers) exhibit higher rather than lower returns, and controlling for profitability improves rather than eliminates the book-to-market effect.[15] In results reported in the Internet Appendix (Table A7), we find that controlling for operating leverage leaves the association between future returns and market-to-value essentially unchanged, and neither market-to-book nor any of the components are significantly exposed to a long-short operating leverage strategy.

Nevertheless, in the presence of operating leverage, market-to-book has a further role in predicting future stock returns, if it reliably picks up variation in assets in place versus growth options, beyond differences in productivity. As operating inflexibility makes assets in place risker than growth options, high market-to-book firms should earn lower expected returns if they have fewer assets in place (holding firm productivity/operating leverage constant). This logic is alluded to in both Novy-Marx (2011) and Zhang (2005), although not formally modelled.

The intuition behind market-to-book capturing variation in assets in place versus growth options is straightforward: the value of growth options should be reflected in market value equity, but not in book value. Numerous studies document relationships that are consistent with market-to-book capturing growth option intensity. Work in corporate finance shows that market-to-book is negatively related to leverage, consistent with growth options having lower (or even negative) debt capacity: growth options have lower collateral value, lower free cash flow benefits of debt, and higher underinvestment costs of debt (see e.g. Rajan and Zingales (1995), Hovakimian, Opler, and Titman (2001), Barclay, Smith, and Morellec (2006)). In addition, Ai, Croce, and Li (2013) show that book-to-market sorts reveal differences in firm age, with growth firms being younger.[16]

[15] Note that market to value is orthogonal to profitability by construction (net income is in the valuation model and market-to-value is the residual). A further control for operating profitability is included in firm-level regressions in Table 4.

[16] Grullon, Lyandres, and Zhdanov (2012) further show that young firms exhibit greater sensitivity to volatility, consistent with young firms having more growth option value.

Ai and Kiku (2016) show that high Q firms exhibit higher sensitivity to idiosyncratic volatility, consistent with high Q firms being more growth-option-intensive. Lastly, Kogan and Papanikolaou (2014) show a negative association between IMC betas and HML betas, consistent with growth option value responding positively to reductions in the exercise price of those options. In light of these associations, the operating inflexibility mechanism in Novy-Marx (2011) and Zhang (2005) may, indeed, account for the value premium.

Since firm-specific error is responsible for the market-to-book effect, a test of the operating inflexibility/operating leverage story boils down to a test of whether market-to-value continues to proxy for the mix of assets in place versus growth options, or whether this variation is passed on to the unpriced components (e.g. if our valuation model captures growth option value). We have already shown that the association between market-to-book and exposure to investment-specific technology shocks of Kogan and Papanikolau (2014) stems from the unpriced value-to-book component. We explore the other proxies in Table 8. Confirming the studies cited above, market-to-book sorts uncover strong and monotonic patterns in firm age (Panel A), leverage (Panel B), and sensitivity to idiosyncratic volatility (Panel C). Differences between value and growth are economically large (e.g. 6.2 years for age, 8.4 percentage points for leverage) and highly statistically significant. However, all of these relations are driven entirely by value-to-book, where the differences are further magnified. Sorting on the priced firm-specific error does not reveal patterns in any of the measures, except for an economically small difference in age of 1.03 years (compared to 10.89 years for value-to-book). Absent differences in growth option intensity across portfolios based on the component of market-to-book that is actually priced, explanations relying on growth-option intensity cannot explain the value premium.[17]

We employ a fourth proxy for the importance of operating leverage, namely fixed asset tangibility (property, plant, and equipment divided by total assets). While it does not obviously

[17] We do not use investment variables (e.g. asset growth or capital expenditure/R&D expenses) as a proxy for growth option intensity, because investment can respond to market-to-book in the presence of mispricing. The RRV market-to-book decomposition was developed specifically to study the link between misvaluation and investment in the form acquisitions. More generally, Binsbergen and Opp (2017) provide evidence of "real" anomalies whereby managers of firms whose stock returns are anomalously low infer that their cost of capital is low and increase investment. Alternatively, if managers learn about investment opportunities from dislocated stock prices, they erroneously infer that investment opportunities are high/low and adjust investment accordingly. In addition, rational managers of financially constrained firms may exploit stock overvaluation to finance investment, and decrease investment to avoid issuing equity at too low a price (Baker, Stein, and Wurgler (2003)). See also Chirinko and Schaller (2001), Gilchrist, Himmelberg, and Huberman (2005), and Polk and Sapienza (2009).

proxy for the mix of assets-in-place vs. growth options, this measure increases with the amount of productive capital that is subject to both i) fixed operating costs, and ii) costly adjustment. In other words, this measure captures the portion of the firm's assets affected by operating leverage, as predicted by theories of Zhang (2005) and Novy-Marx (2011).[18] Panel D presents the results. We find that market-to-book sorts uncover large differences in the amount of capital affected by operating leverage. Tangible fixed assets represent 36% of total assets for value firms and 26% for growth firms. The difference of almost 10 percentage points is economically large. However, this difference is driven entirely by value-to-book; in fact, the spread in asset tangibility across value-to-book sorted portfolios widens to a 16.5 percentage points. Total error and firm-specific error exhibit U-shaped patterns in fixed asset tangibility with virtually zero differences between the extreme portfolios. Asset tangibility across sector error portfolios is virtually constant. Once again, there are no differences in the amount of capital affected by operating leverage across the component of market-to-book that earns a premium.[19]

[Please Insert Table 8 about Here]

Finally, note that the findings in this section also pose a challenge to duration-based explanations of the value premium (e.g., Lettau and Wachter (2007)). Since assets in place produce cash flows today, while growth options can only produce cash flows in the future, the variation in the timing of cash flows should be associated with variation in the mix of assets in place versus growth options. Our results show that there is no such variation across market-to-value portfolios. We provide further tests of the duration-based explanation in the following section.

V.E Duration

Another risk-based explanation for the value premium appeals to the differential timing of cash flows among value and growth firms; cash flows of growth firms are realized in the more

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[18] Current assets such as cash and short-term investments are easily adjusted to changes in demand. Purchases of inventory (raw materials) can be reduced when demand is low; accounts receivable will also adjust together with demand. Intangible assets such as patents, copyrights, trademarks, distribution rights, and software licenses might be costly to adjust but do not entail fixed operating costs.

[19] The model in Novy-Marx (2011) also predicts that market-to-book should have a stronger effect when operating leverage is high, because assets in place are particularly risky when operating leverage is high (see Eq. (2) and Fig. 1 in his paper). We conduct these tests using double sorts on market-to-book or its components and industry operating leverage. Consistent with no variation in growth option intensity across market-to-value, these double sorts reveal no robust differential effects of market-to-book or firm-specific error across operating leverage quintiles.

distant future than those of value firms. Lettau and Wachter (2007) argue theoretically that long-horizon equity is less risky than short-horizon equity, and that this can potentially provide an explanation for the value premium. Dechow, Sloan, and Soliman (2004) develop an empirical measure of equity duration implied by the stock price and show that growth firms, indeed, have longer cash flow durations. They further show that a low-minus-high duration factor exhibits a significant positive return.

One limitation of the implied equity duration measure is that it is a function of the stock price, making it difficult to disentangle market-to-book from duration. Da (2009) proposes a portfolio-level measure of duration based solely on accounting fundamentals, and continues to find that cash flows of growth portfolios have longer duration than those of value portfolios. Chen (2017) further shows that dividends of growth stocks in buy-and-hold portfolios grow faster than those of value stocks in the modern sample period, albeit the difference is not large enough to fully explain the value premium.

We employ our decomposition to shed light on the association between the value premium and cash flow duration. Being price-scaled variables, market-to-book, market-to-value and implied equity duration are naturally expected to covary, generating mechanical associations. Moreover, duration metrics that rely on stock prices are influenced by possible mispricing, and therefore cannot be used to distinguish between risk and mispricing explanations for the value premium.[20]

Since our decomposition offers an alternative valuation for the stock (i.e. our estimate of fundamental value *v)*¸ it is natural to examine a measure of duration implied by this alternative price. We follow the exact methodology of Dechow, Sloan, and Soliman (2004) to compute implied equity duration, after replacing stock price with our measure of intrinsic value *v.* Although this new measure has the benefit of being independent of the stock price, it does require our model to properly value future growth. Results, reported in Panel A of Table 9, show that extreme market-to-book portfolios continue to exhibit large and significant differences in duration. However, extreme portfolios formed on the basis of total error and firm-specific error exhibit differences in

[20] Indeed, Weber (2017) shows that returns of the duration strategy based on this measure come from stocks that are difficult to arbitrage, concentrate in periods following high investor sentiment, and that analysts have overly optimistic growth forecasts for high duration stocks that they adjust downward over time – evidence that makes him lean towards a mispricing-based explanation of the returns to this strategy. Our subsequent tests show that market-to-book and market-to-value strategies have similar features. Nevertheless, including implied equity duration as an additional control in firm-level regressions does not subsume the return predictability of total error or firm-specific error (Table A8 of the Internet Appendix).

cash flow duration of the opposite sign, i.e. low market-to-value stocks have somewhat *longer* cash flow durations than high market-to-value stocks. Sector error follows the same pattern. As is the case with most of our tests, value-to-book is responsible for entire duration spread in market-to-book portfolios, where the difference is further magnified.[21]

We now resort to more direct measures of cash flow duration. Da (2009) proposes a portfolio-level measure of cash flow duration that requires only accounting fundamentals. Specifically, Da (2009) defines duration as an infinite sum of discounted dividend growth rates and finds that value portfolios have shorter cash flow durations than growth portfolios. We follow the methodology of Da (2009) after accounting for two biases pointed out by Chen (2017). First, Chen (2017) recommends omitting the first-year (look-back) growth rate from the infinite sum, since the concept of cash flow duration pertains only to the timing of *future* cash flows.[22] Second, to approximate growth rates beyond year 7, Da uses the average return on equity (ROE) of years 1-7. However, Chen (2017) points out that value and growth firms' earnings diverge significantly around portfolio formation, but gradually converge towards each other, stabilizing around year 7. Therefore, the average ROE of years 1-7 overestimates the steady-state earnings for growth stocks and understates the steady-state earnings for value stocks. We use year 7 earnings in constructing our terminal value, to allow for such convergence to occur.[23] Panel B of Table 9 reports the results.

Consistent with Da (2009), we confirm that value portfolios have significantly shorter cash flow duration than growth portfolios. However, once we decompose market-to-book into the various components, we find that value-to-book is solely responsible for this association, and the spread across low and high value-to-book portfolios is further strengthened. Extreme portfolios formed on the basis of total error and firm-specific error exhibit no significant differences in cash flow duration. Thus, while the cash flows of value stocks have shorter duration than growth stocks according to the modified Da (2009) measure, this is not the case for the component of market-to-book that drives return predictability.

[21] In unreported results we also find that a duration measure implied by v is not priced in the cross-section. We therefore do not examine covariances of strategies' returns with a factor based on this measure.

[22] Consider two firms with cash flows of 5, 10, 15, 20, 25, 30 and 10, 10, 15, 20, 25, 30 paid out during years 0, 1, 2, 3, 4, 5, respectively. At the end of year 0 (portfolio formation date), these two firms have identical future cash flows (years 1-5) and thus identical cash flow durations. Inclusion of the first (look-back) growth rate would result in a higher duration measure for the first firm, which is counterfactual.

[23] The results are robust to using the average of years 6 and 7.

Finally, we consider the results in Chen (2017) who shows, among others, that dividends of growth stocks grow somewhat faster than dividends of value stocks in the modern sample period, albeit the difference is not large enough to fully explain the magnitude of the value premium. Panel C of Table 9 reports Chen's baseline results, namely, the geometric average growth rate in dividends of buy-and-hold portfolios from years 1 to 10 following portfolio formation. We find a statistically significant difference in the geometric average dividend growth rate of about -2.4% between low and high market-to-book portfolios, similar to the magnitude reported by Chen (2017). Indeed, growth stocks' dividends grow somewhat faster than value stocks, implying longer cash flow duration. As for the components, this difference is virtually zero for total error and firm-specific error. Sector error exhibits a small positive but statistically insignificant difference. Value-to-book, however, exhibits a sizeable difference in the geometric average growth rate in dividends of -4.55% and highly statistically significant. These results do not change when using VW portfolios (Table A8 of Internet Appendix). Therefore, even the modest difference in growth rates between value and growth stocks found by Chen (2017) is driven by value-to-book and not by the component that is responsible for the return premium.

[Please Insert Table 9 about Here]

Overall, our results show no differences in duration across portfolios sorted on the component of market-to-book that exhibits return predictability. Therefore, duration is unlikely to be the reason behind the value premium. Once again, we do not take a stance on whether duration itself – independently of the value premium – is a priced source of risk. Our conclusions are only with respect to its ability to explain the value premium.

V.F Analyst Risk Ratings

There is evidence that equity research analysts perceive value stocks to be risky. Lui, Markov, and Tamayo (2007) show that analysts' risk ratings correlate negatively with market-to-book, while Lui, Markov, and Tamayo (2012) further show that changes in analysts' risk ratings move stock prices and are followed by changes in Fama-French factor loadings. In order to speak to this type of risk-based evidence for the value premium, we obtain analysts' risk ratings data from a major equity research provider and replicate these tests on the decomposed market-to-book. In their research reports, equity analysts assign stocks a rating of "Low Risk", "Medium Risk", "High Risk", and "Speculative Risk", which we convert to numerical ranks 1, 2, 3, and 4, respectively. These ratings are assigned monthly but contain very little variation during the year; hence we convert the data to stock-year observations and use the rating in June consistent with portfolio formation. The sample period is from 2003 to 2010. We regress these risk ratings on market-to-book or its components, as well as other characteristics shown to affect these risk ratings. We follow Lui, Markov, and Tamayo (2007) and estimate pooled ordered logit regressions with year fixed effects. Standard errors are clustered at the firm level. The results are reported in Table 10.

Column (1) uses the conventional market-to-book as the sole explanatory variable. Consistent with Lui, Markov, and Tamayo (2007), we find that analysts' risk ratings correlate negatively with market-to-book. Columns (2) and (3) use the two-part and three-part decompositions, respectively. The correlation of analysts' risk ratings with market-to-book is driven entirely by the value-to-book component. Analysts do not perceive firm-specific error to be risky – yet this is the priced part of market-to-book. Whatever risk the analysts have in mind with respect to market-to-book, this risk does not earn a return premium. Columns (4), (5), and (6) include other determinants of analysts' risk ratings, namely size, market beta, illiquidity, idiosyncratic volatility, and leverage. The conventional market-to-book remains significant after adding controls (albeit only marginally). Once again, this relation is driven by the value-to-book component. Overall, the evidence in this section shows that the risk in value stocks as perceived by equity research analysts is concentrated in the part of market-to-book that is not associated with a risk premium.

[Please Insert Table 10 about Here]

Overall, our results are at odds with most risk-based evidence on the value premium. These conclusions echo those of Phalippou (2007), who argues that prominent risk-based theories cannot explain the value premium as the results are sensitive to the choice of test assets. We now turn to the behavioral explanations and revisit some of the early evidence through our decomposition.

VI. Behavioral Explanations

VI.A Expectational Errors and Overextrapolation

In this part of the paper we test whether the results in prior literature linking value/growth to expectational errors are, indeed, due to market-to-value – the component of market-to-book exhibiting return predictability. If stocks characterized by positive (negative) deviations of market prices from implied fundamental values exhibit lower (higher) subsequent performance due to corrections of over-(under)valuation, investors should be negatively (positively) surprised by the realization of fundamentals of high (low) market-to-value firms following portfolio formation. Therefore, we perform earnings announcement surprise tests conditional on market-to-book and its components. The same test is performed by La Porta et al. (1997) for the conventional market-to-book ratio. Table 11 reports the results.

Specifically, we measure excess returns based on the market model over the window (–5, +5) centered on the quarterly earnings announcement date, and then aggregate these abnormal returns over the 4 quarters *following* portfolio formation.[24] These tests are slightly complicated by the fact that firms have different fiscal year ends. Since we form our portfolios on June 30, the actual quarters entering the calculation differ depending on the first reporting quarter on or after June 30.[25] Panel A of Table 11 reports the results. We find that low market-to-book stocks exhibit positive earnings surprises in the year following portfolio formation, while high market-to-book stocks exhibit negative earnings surprises. The difference between high and low deciles is economically large and highly statistically significant. These results are consistent with the findings of La Porta et al. (1997). When we break up the market-to-book ratio into its components, we find that virtually all of this result is driven by the market-to-value component, and, in particular, by firm-specific error.

Our evidence indicates that investors are negatively surprised by the realization of fundamentals of high market-to-value firms and positively surprised by the news of low market-to-value firms. These effects are consistent with the behavioral explanations for the value premium. However, for these explanations to be complete, one needs to establish i) a mechanism by which stocks become over-/undervalued, and ii) the market friction(s) that allows such stock price dislocations to persist for prolonged periods of time. This is what we attempt to do next.

One potential mechanism for relative over-/undervaluation to arise is investors' overextrapolation of recent good or bad news. If this is how stock prices deviate from fundamental values, we should find that high (low) market-to-book and market-to-value stocks actually report

[24] The results are robust to using shorter event windows and to using simple market-adjusted returns.

[25] For a firm with fiscal year end in December 2000, we look at earnings announcement dates that relate to quarters 06/01, 09/01, 12/01 and 03/02. Correspondingly, for a firm with fiscal year end in March 2000, we look at earnings announcement dates for the quarters 06/00, 09/00, 12/00 and 03/01. Similarly, for all other fiscal year end firms we look at the 4 announcement dates that follow portfolio formation.

good (bad) news in the quarters prior to portfolio formation. To test this conjecture, we repeat our earnings surprise tests but this time looking at four quarters *prior to* portfolio formation. Panel B of Table 11 presents the results. Indeed, we find that the post-portfolio-formation pattern is reversed: low market-to-book stocks exhibit negative earnings surprises, and high market-to-book stocks exhibit positive earnings surprises. Once again, this pattern is driven by the market-to-value component and not by the value-to-book component. That is, stocks whose prices are above fundamental values reported good news in the quarters prior to portfolio formation, and vice versa. This suggests that a potential mechanism by which stocks become overvalued (undervalued) is investors overextrapolation of recent good (bad) news. This is in the spirit of Lakonishok, Shleifer, and Vishny (1994) who show that value firms tend to exhibit lower prior growth in accounting fundamentals.

[Please Insert Table 11 about Here]

A remaining question, however, is why mispricing (if any) is not corrected by arbitrageurs. After all, our market-to-book decomposition relies on information that is publicly available to investors at the time of portfolio formation. Typical explanations for the persistence of mispricing in financial markets revolve around limits to arbitrage (Shleifer and Vishny (1997)). In fact, existing studies show that the value strategy return is largely due to stocks characterized by limits to arbitrage. In the next section we explore whether these results arise due to the market-to-value component.

VI.B Limits to Arbitrage

One potential limit to arbitrage is short sale constraints. If arbitrageurs cannot short sell the overpriced securities, then they cannot profit from overvaluation, or hedge their long positions in underpriced securities. Another limit to arbitrage is noise trader risk. Specifically, even if the arbitrageur is correct in her assessment of mispricing over the medium term, she may be forced to liquidate her position prematurely if stock price moves against the arbitrageur in the short-term before ultimately correcting to fundamental value (the so-called "noise trader risk"). If limits to arbitrage is the mechanism by which mispricing persists over time, we should find that the performance of the market-to-book and market-to-value strategies are more pronounced in securities characterized by short sale constraints and/or noise trader risk.

To test the short sale constraints proposition, we use institutional ownership as our proxy for short sale constraints. Nagel (2005) argues that institutional investor ownership enables short selling by increasing the supply of lendable shares and shows that the market-to-book effect is stronger for stocks characterized by low institutional ownership. Table 12 reports the results using institutional ownership and RW portfolios. In Panel A we implement two-way sorts based on market-to-book and the level of (residual) institutional ownership, resulting in 25 portfolios. The long-short return of the market-to-book strategy for low institutional ownership produces a monthly hedge return of 0.80. The same long-short strategy for stocks with high institutional ownership produces a hedge return only about half the size: 0.44% per month. Importantly, the difference arises largely due to *high* market-to-book stocks – those that would be considered overpriced and thus affected by short sale constraints. In Panels B to E we repeat these tests on the components of market-to-book and find that the above pattern is entirely due to market-to-value (total error in Panel B; firm-specific error in Panel C). Again, these patterns are driven by high market-to-value stocks – the ones that need to be sold short and thus most affected by short sale constraints. The above patterns are not there for value-to-book.

When using VW portfolios (Table A9 of the Internet Appendix), we further split the universe into small and big stocks: Nagel (2005) shows that institutional ownership does not affect the value premium for large stocks, suggesting that large stocks tend to be available for shorting regardless of institutional ownership. This means that VW portfolios will tend to work against finding this interaction effect. As expected, the differential market-to-book and market-to-value effects across institutional ownership quintiles are detectable in small but not in large stocks when portfolios are value-weighted.

[Please Insert Table 12 about Here]

Overall, there is evidence that the value premium is concentrated in stocks with relatively high short sale constraints, and that this finding is due to market-to-value. We now turn to the noise trader risk proposition as an additional limit to arbitrage explanation for why stock price dislocations may persist for prolonged periods of time.

Noise trader risk is the possibility that, in the short run, stock prices may deviate even further from fundamental value and move against the arbitrageur, causing arbitrageurs' capital providers – who are unable to tell noise from actual mistakes – to withdraw capital at the time when it is needed the most. Ali, Hwang, and Trombley (2003) use idiosyncratic stock return volatility as proxy for arbitrage risk and show that the market-to-book strategy return is greater for the set of stocks with high idiosyncratic return volatility.

We replicate these tests on the conventional market-to-book and then on our components. Table 13 presents the results using RW portfolios. Panel A shows that the long-short return of the market-to-book strategy is appreciably greater for the high idiosyncratic volatility stocks than for the low idiosyncratic volatility stocks (0.69% per month versus only 0.24% per month). Panels B and C show that these differences are even more pronounced when the stocks are sorted on the basis of the market-to-value component (total error or firm-specific error). Finally, the results in Panel E show no such difference when stocks are sorted on the basis of value-to-book. In VW portfolios (Table A10 of the Internet Appendix) we continue to find that the market to-book and market-to-value effects are concentrated in high idiosyncratic volatility stocks, and that this holds for small but not for large stocks. Therefore, there is evidence that the high (low) subsequent returns of stocks whose market values are below (above) estimated fundamental values are concentrated in stocks characterised by significant noise trader risk.

[Please Insert Table 13 about Here]

Overall, the results reported in this section provide evidence that the market-to-book effect – driven entirely by the market-to-value component – is concentrated in the set of stocks characterized by limits to arbitrage. This is consistent with the proposition that the value/growth dimension captures stock price deviations from fundamental value that cannot be immediately arbitraged away.

VI.C A New Time-Series Test: Arbitrage Capital Availability

Finally, we conduct a novel time-series test of the limits to arbitrage story. Kokkonen and Suominen (2015) show that hedge fund assets under management serve as a good proxy for the availability of arbitrage capital. They show that the returns of an anomaly based on residual income valuation model are higher in periods of low arbitrage capital availability. Jylhä and Suominen (2011) further relate arbitrage capital availability to carry trade returns. If the value strategy returns are due to stock price dislocations, we should find that the return predictability of market-to-book (as driven by market-to-value) is higher when arbitrage capital at portfolio formation is low.

We follow Jylhä and Suominen (2011) and Kokkonen and Suominen (2015) and proxy for arbitrage capital availability with hedge funds assets under management (HF AUM).[26] These data represent monthly observations on HF AUM, scaled by the average CRSP market capitalization over the previous 12 months. The data are available to us from January 1990 to December 2011, so these tests are limited to the late sample period. HF AUM exhibits an upward trend over time, starting at around 1.5% in January 1990 and increasing to about 15.0% at the end of 2011, with meaningful variation in between. We divide the 22 sample years for which we have data – corresponding to 22 portfolio formations – into three periods based on HF AUM in June: low (84 months), medium (96 months), and high (84 months).[27] We then examine the performance of our strategies conditional on arbitrage capital availability. Table 14 presents the results using RW portfolios.

The magnitude of the hedge portfolio return for the usual value strategy (Panel A) during the period of low arbitrage capital availability is higher than that during the period of high arbitrage capital availability, although the difference is not statistically significant at conventional levels. Moving to the strategy based on total error (Panel B), the above pattern becomes more pronounced: the hedge return of the total error strategy is 1.209% and statistically significant during the low arbitrage capital availability period, and only 0.497% and statistically insignificant during the high arbitrage capital availability period (albeit the difference between the two hedge returns is still not statistically significant). This result is further strengthened in Panel C, where the strategies are based on firm-specific error: the difference in the hedge returns between low and high arbitrage capital availability periods is 0.936% with a p-value of 0.105. Strategies on the basis of sector error and long-run value-to-book do not exhibit such patterns. Tests using VW portfolios yield very similar results (Table A11 of the Internet Appendix). Overall, the return predictability of the conventional value strategy is driven by the market-to-value component and is concentrated in periods of low arbitrage capital availability. These results are consistent with the proposition that the value effect arises from stock price dislocations from fundamental value and subsequent corrections.

[Please Insert Table 14 about Here]

[26] We thank Petri Jylha and Joni Kokkonen for sharing these data with us.

[27] The years of low HF AUM are 1990-1993 and 1999-2001; the years of medium HF AUM are 1994-1998 and 2002-2004, and the years of high HF AUM are 2005-2011.

VII. Further Robustness Tests

VII.A Refining the Valuation Model: Industry Definitions

Throughout our analysis we have kept our industry definitions fairly broad (Fama-French 12) in order to ensure a sufficient number of firms for each industry-year (for our cross-sectional valuation models to be meaningful). A potential concern is that the 12 Fama-French industry classification is too broad to capture differences in corporate valuations, and that our decomposition may erroneously attribute this unexplained variation to over/undervaluation. We therefore experiment with finer industry classifications, but at the expense of having to drop industries that do not contain at least 30 firms in each year. We have replicated our main predictability results for Fama-French 30 (21 industries remain) and 38 (14 industries remain), as well as Campbell (1996) 12 industry classifications. These results are reported in Tables A13-A15 in the Internet Appendix. We continue to find that the market-to-value component drives all of the return predictability in both portfolio sorts and firm-level returns regressions with controls.

VII.B Refining the Valuation Model: The Impact of Growth

Despite the valuation model in equation (4) doing a good job at explaining the variation in market values (R^2 of 80-90%), we experiment with augmenting it with other value relevant variables. The growing perpetuity discounted cash flow valuation model *V=CF/(r-g)* suggests that market values should be a function of profitability and growth. While we have a proxy for the former in the model (net income), we incorporate growth indirectly via the industry valuation coefficients. Therefore, we augment the model with a direct firm-level proxy for growth:

$$m_{it} = \alpha_{0jt} + \alpha_{1jt}b_{it} + \alpha_{2jt}ni^{+}_{it} + \alpha_{3jt}I_{(<0)}(ni^{+}_{it}) + \alpha_{4jt}LEV_{it} + \alpha_{5jt}Growth_{it} + \varepsilon_{t}, \tag{5}$$

where $Growth_{it}$ is a 3-year growth in sales from year *t*-3 to year *t*. For brevity, we only report the main portfolio sorts and coefficients from the firm-level return regression results (Table A16 in the Internet Appendix). We do note however that the coefficient α_5 in the valuation model is consistently positive across industries, suggesting that firms on faster earnings growth trajectories have higher valuations. Interestingly, the addition of the growth variable contributes very little to the overall explanatory power of the model (the R^2s improve only by up to 1%), suggesting that other aspects of the model are already capturing certain dimensions of growth. Overall, the results demonstrate that the addition of growth to the valuation model does not change any of our conclusions – it is the market-to-value component that continues to drive return predictability, while value-to-book does not.

VIII. Conclusion

Using the market-to-book decomposition of Rhodes–Kropf, Robinson, and Viswanathan (2005) we show that all of the value premium is concentrated in the market-to-value component; value-to-book has no explanatory power for the cross-section of stock returns in either portfolio sorts or firm-level return regressions.

While prior literature has found that portfolios formed on the basis of market-to-book are picking up differential exposure to cash flow risk, long-run consumption risk, investment-specific technology shocks, operating leverage and duration, we find that these results do not hold for market-to-value with two notable exceptions: the bad beta of Campbell and Vuoltenaaho (2004) and the ultimate consumption risk of Parker and Julliard (2005). The use of realized returns to measure covariances is critical for these exceptions. In all other cases, existing evidence on risk-based origins of the value premium is due to the unpriced value-to-book component.

We further find that high (low) market-to-value stocks are characterized by positive (negative) earnings surprises in the quarters prior to portfolio formation, and negative (positive) earnings surprises in the quarters following portfolio formation. This pattern can be consistent with investors overextrapolating good (bad) news of high (low) market-to-value stocks, leading to temporary stock price deviations from intrinsic value that are subsequently corrected as the true fundamentals are revealed. We also show that the market-to-value strategy return is concentrated in stocks characterized by limits to arbitrage – short sale constraints and noise trader risk, which allows deviations from intrinsic value to persist for prolonged periods of time. Similarly, the return predictability of the market-to-book and market-to-value strategies is concentrated in periods of low arbitrage capital availability. None of the above patterns hold for value-to-book.

Overall, our evidence casts doubt on most prominent risk-based explanations for the value premium, subject to the usual joint hypothesis problem of the pricing model being true and the estimated risk loadings properly capturing the variation of interest. While our tests cannot rule out all potential risk-based explanations, any such theory would have to offer very nuanced cross-sectional predictions across several dimensions documented in this paper.

REFERENCES

Ai, Hengjie, Mariano Massimiliano Croce, and Kai Li, 2013, Toward a quantitative general equilibrium asset pricing model with intangible capital, *Review of Financial Studies* 26, 491-530.

Ai, Hengjie, and Dana Kiku, 2016, Volatility risks and growth options, *Management Science* 62, 741-763.

Ali, Ashiq, Lee-Seok Hwang, and Mark A. Trombley, 2003, Arbitrage risk and the book-to-market anomaly, *Journal of Financial Economics* 69, 355-373.

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31-56.

Ang, Andrew, Joseph Chen, and Yuhang Xing, 2006, Downside risk, *Review of Financial Studies* 19, 1191-1239.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259-299.

Asness, Clifford S., Tobias J. Moskowitz, and Lasse Heje Pedersen, 2013, Value and momentum everywhere, *Journal of Finance* 68, 929-985.

Baker, Malcolm, Jeremy C. Stein, and Jeffrey Wurgler, 2003, When does the market matter? Stock prices and the investment of equity-dependent firms, *Quarterly Journal of Economics* 118, 969-1005.

Ball, Ray, Joseph Gerakos, Juhani T. Linnainmaa, and Valeri V. Nikolaev, 2015, Deflating profitability, *Journal of Financial Economics* 117, 225-248.

Bansal, Ravi, Robert F. Dittmar, and Christian T. Lundblad, 2005, Consumption, dividends, and the cross section of equity returns, *Journal of Finance* 60, 1639-1672.

Banz, Rolf W., 1981, The relationship between return and market value of common stocks, *Journal of Financial Economics* 9, 3-18.

Barber, Brad M., and John D. Lyon, 1997, Firm size, book-to-market ratio, and security returns: A holdout sample of financial firms, *Journal of Finance* 52, 875-883.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny, 1998, A model of investor sentiment, *Journal of Financial Economics* 49, 307-343.

Barclay, Michael J., Clifford W. Jr. Smith, and Erwan Morellec, 2006, On the debt capacity of growth options, *Journal of Business* 79, 37-59.

Binsbergen, Jules H. van, and Christian Opp, 2017, Real anomalies, *Journal of FInance* forthcoming.

Campbell, John Y., 1996, Understanding risk and return, *Journal of Political Economy* 104, 298.

Campbell, John Y., Jens Hilscher, and Jan Szilagyi, 2008, In search of distress risk, *Journal of Finance* 63, 2899-2939.

Campbell, John Y., and Tuomo Vuolteenaho, 2004, Bad beta, good beta, *American Economic Review* 94, 1249-1275.

Carlson, Murray, Adlai Fisher, and Ron Giammarino, 2004, Corporate investment and asset price dynamics: Implications for the cross-section of returns, *Journal of Finance* 59, 2577-2603.

Chen, Huafeng, 2017, Do cash flows of growth stocks really grow faster?, *Journal of Finance* 72, 2279-2330.

Chen, Long, and Xinlei Zhao, 2009, Return decomposition, *Review of Financial Studies* 22, 5213-5249.

Chirinko, Robert S., and Huntley Schaller, 2001, Business fixed investment and "bubbles": The japanese case, *American Economic Review* 91, 663-680.

Cohen, Randolph B., Christopher Polk, and Tuomo Vuolteenaho, 2009, The price is (almost) right, *Journal of Finance* 64, 2739-2782.

Conrad, Jennifer, Michael Cooper, and Gautam Kaul, 2003, Value versus glamour, *Journal of Finance* 58, 1969-1996.

Cooper, Michael J., Huseyin Gulen, and Michael J. Schill, 2008, Asset growth and the cross-section of stock returns, *Journal of Finance* 63, 1609-1651.

Da, Zhi, 2009, Cash flow, consumption risk, and the cross-section of stock returns, *Journal of Finance* 64, 923-956.

Da, Zhi, and Pengjie Gao, 2010, Clientele change, liquidity shock, and the return on financially distressed stocks, *Journal of Financial & Quantitative Analysis* 45, 27-48.

Da, Zhi, and Mitchell Craig Warachka, 2009, Cashflow risk, systematic earnings revisions, and the cross-section of stock returns, *Journal of Financial Economics* 94, 448-468.

Daniel, Kent D., David Hirshleifer, and Avanidhar Subrahmanyam, 2001, Overconfidence, arbitrage, and equilibrium asset pricing, *Journal of Finance* 56, 921-965.

Daniel, Kent, and Sheridan Titman, 2006, Market reactions to tangible and intangible information, *Journal of Finance* 61, 1605-1643.

Davis, James L., Eugene F. Fama, and Kenneth R. French, 2000, Characteristics, covariances, and average returns: 1929 to 1997, *Journal of Finance* 55, 389-406.

De Long, J. Bradford, Andrei Shleifer, Lawrence H. Summers, and Robert J. Waldmann, 1990, Noise trader risk in financial markets, *Journal of Political Economy* 98, 703.

Dechow, Patricia M., Richard G. Sloan, and Mark T. Soliman, 2004, Implied equity duration: A new measure of equity risk, *Review of Accounting Studies* 9, 197-228.

Fama, Eugene F., 1991, Efficient capital markets: II, *The Journal of Finance* 46, 1575-1617.

Fama, Eugene F., 1998, Market efficiency, long-term returns, and behavioral finance, *Journal of Financial Economics* 49, 283-306.

Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 47, 427-465.

Fama, Eugene F., and Kenneth R. French, 1998, Value versus growth: The international evidence, *Journal of Finance* 53, 1975-1999.

Fama, Eugene F., and Kenneth R. French, 2008, Average returns, b/m, and share issues, *Journal of Finance* 63, 2971-2995.

Fama, Eugene F., and Kenneth R. French, 2012, Size, value, and momentum in international stock returns, *Journal of Financial Economics* 105, 457-472.

Fama, Eugene F., and Kenneth R. French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1-22.

Fu, Fangjian, Leming Lin, and Micah S. Officer, 2013, Acquisitions driven by stock overvalution: Are they good deals?, *Journal of Financial Economics* 109, 24-39.

Gerakos, Joseph, and Juhani T. Linnainmaa, 2017, Decomposing value, *Review of Financial Studies* forthcoming.

Gilchrist, Simon, Charles P. Himmelberg, and Gur Huberman, 2005, Do stock price bubbles influence corporate investment?, *Journal of Monetary Economics* 52, 805-827.

Gomes, João F., Leonid Kogan, and Motohiro Yogo, 2009, Durability of output and expected stock returns, *Journal of Political Economy* 117, 941-986.

Griffin, John M., and Michael L. Lemmon, 2002, Book–to–market equity, distress risk, and stock returns, *Journal of Finance* 57, 2317-2336.

Grullon, Gustavo, Evgeny Lyandres, and Alexei Zhdanov, 2012, Real options, volatility, and stock returns, *Journal of Finance* 67, 1499-1537.

Harvey, Campbell R., Yan Liu, and Heqing Zhu, 2016, ... and the cross-section of expected returns, *Review of Financial Studies* 29, 5-68.

Hertzel, Michael, and Zhi Li, 2010, Behavioral and rational explanations of stock price performance around SEOs: Evidence from a decomposition of market-to-book ratios, *Journal of Financial & Quantitative Analysis* 45, 935-958.

Hou, Kewei, Mathijs A. van Dijk, and Yinglei Zhang, 2012, The implied cost of capital: A new approach, *Journal of Accounting & Economics* 53, 504-526.

Hovakimian, Armen, Tim Opler, and Sheridan Titman, 2001, The debt-equity choice, *Journal of Financial & Quantitative Analysis* 36, 1-24.

Jegadeesh, Narasimhan, 1990, Evidence of predictable behavior of security returns, *Journal of Finance* 45, 881-898.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65-91.

Jensen, Michael C., 2005, Agency costs of overvalued equity, *Financial Management* 34, 5-19.

Jylhä, Petri, and Matti Suominen, 2011, Speculative capital and currency carry trades, *Journal of Financial Economics* 99, 60-75.

Kogan, Leonid, and Dimitris Papanikolaou, 2014, Growth opportunities, technology shocks, and asset prices, *Journal of Finance* 69, 675-718.

Kokkonen, Joni, and Matti Suominen, 2015, Hedge funds and stock market efficiency, *Management Science* 61, 2890-2904.

La Porta, Rafael, Josef Lakonishok, Andrei Shleifer, and Robert Vishny, 1997, Good news for value stocks: Further evidence on market efficiency, *Journal of Finance* 52, 859-874.

Lakonishok, Josef, Andrei Shleifer, and Robert W. Vishny, 1994, Contrarian investment, extrapolation, and risk, *The Journal of Finance* 49, 1541-1578.

Lettau, Martin, and Jessica A. Wachter, 2007, Why is long-horizon equity less risky? A duration-based explanation of the value premium, *Journal of Finance* 62, 55-92.

Lewellen, Jonathan, Stefan Nagel, and Jay Shanken, 2010, A skeptical appraisal of asset pricing tests, *Journal of Financial Economics* 96, 175-194.

Li, Kevin, and Partha Mohanram, 2014, Evaluating cross-sectional forecasting models for implied cost of capital, *Review of Accounting Studies* 19, 1152-1185.

Lo, Andrew W., and A. Craig MacKinlay, 1990, Data-snooping biases in tests of financial asset pricing models, *Review of Financial Studies* 3, 431-467.

Lui, Daphne, Stanimir Markov, and Ane Tamayo, 2007, What makes a stock risky? Evidence from sell-side analysts' risk ratings, *Journal of Accounting Research* 45, 629-665.

Lui, Daphne, Stanimir Markov, and Ane Tamayo, 2012, Equity analysts and the market's assessment of risk, *Journal of Accounting Research* 50, 1287-1317.

Maksimovic, Vojislav, Gordon Phillips, and Liu Yang, 2013, Private and public merger waves, *Journal of Finance* 68, 2177-2217.

Nagel, Stefan, 2005, Short sales, institutional investors and the cross-section of stock returns, *Journal of Financial Economics* 78, 277-309.

Novy-Marx, Robert, 2011, Operating leverage, *Review of Finance* 15, 103-134.

Novy-Marx, Robert, 2013, The other side of value: The gross profitability premium, *Journal of Financial Economics* 108, 1-28.

Parker, Jonathan A., and Christian Julliard, 2005, Consumption risk and the cross section of expected returns, *Journal of Political Economy* 113, 185-222.

Phalippou, Ludovic, 2007, Can risk-based theories explain the value premium?, *Review of Finance* 11, 143-166.

Piotroski, Joseph D., and Eric C. So, 2012, Identifying expectation errors in value/glamour strategies: A fundamental analysis approach, *Review of Financial Studies* 25, 2841-2875.

Polk, Christopher, and Paola Sapienza, 2009, The stock market and corporate investment: A test of catering theory, *Review of Financial Studies* 22, 187-217.

Pontiff, Jeffrey, 2006, Costly arbitrage and the myth of idiosyncratic risk, *Journal of Accounting & Economics* 42, 35-52.

Rajan, Raghuram G., and Luigi Zingales, 1995, What do we know about capital structure? Some evidence from international data, *Journal of Finance* 50, 1421-1460.

Rhodes-Kropf, Matthew, and S. Viswanathan, 2004, Market valuation and merger waves, *Journal of Finance* 59, 2685-2718.

Rhodes–Kropf, Matthew, David T. Robinson, and S. Viswanathan, 2005, Valuation waves and merger activity: The empirical evidence, *Journal of Financial Economics* 77, 561-603.

Shleifer, Andrei, and Robert W. Vishny, 1997, The limits of arbitrage, *Journal of Finance* 52, 35-55.

Shleifer, Andrei, and Robert W. Vishny, 2003, Stock market driven acquisitions, *Journal of Financial Economics* 70, 295-311.

Shumway, Tyler, 1997, The delisting bias in CRSP data, *Journal of Finance* 52, 327-340.

Shumway, Tyler, and Vincent A. Warther, 1999, The delisting bias in CRSP's Nasdaq data and its implications for the size effect, *Journal of Finance* 54, 2361-2379.

Titman, Sheridan, K. C. John Wei, and Feixue Xie, 2004, Capital investments and stock returns, *Journal of Financial & Quantitative Analysis* 39, 677-700.

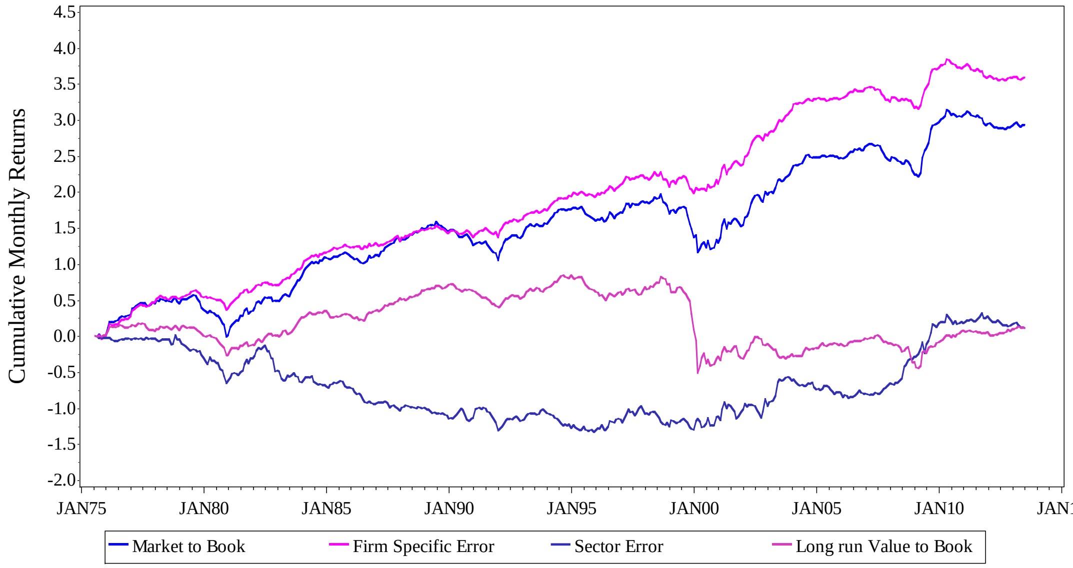
Vuolteenaho, Tuomo, 2002, What drives firm-level stock returns?, *Journal of Finance* 57, 233-264.

Weber, Michael, 2017, Cash flow duration and the term structure of equity returns, *Journal of Financial Economics* forthcoming.

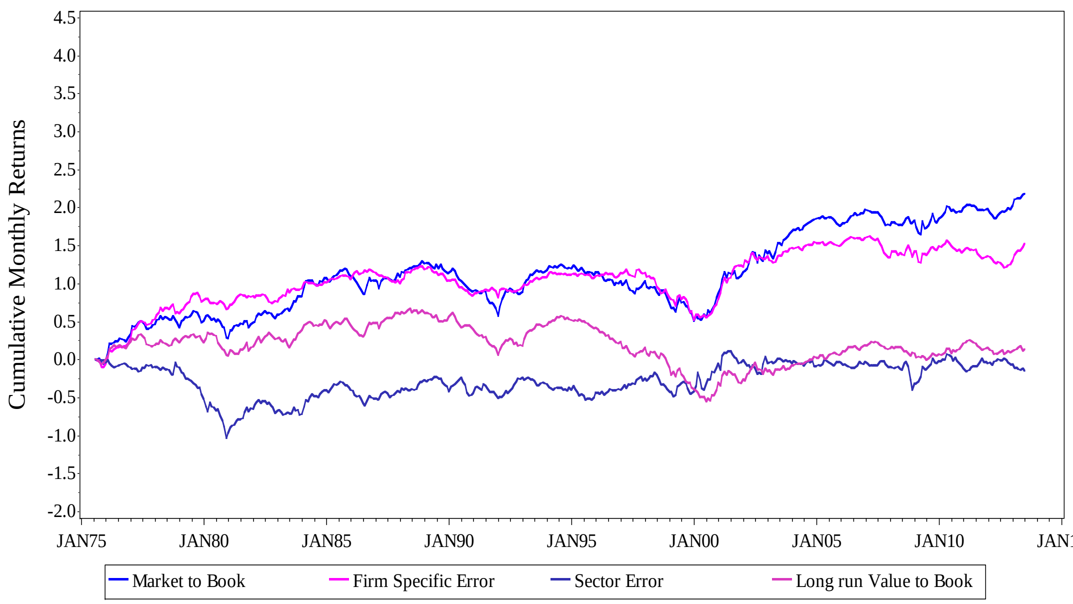
Zhang, Lu, 2005, The value premium, *Journal of Finance* 60, 67-103.

FIGURE 1
Calendar-time cumulative monthly returns of long/short strategies

Panel A: RW Portfolios



Panel B: VW Portfolios



This figure plots the cumulative performance of long-short strategies based on log market-to-book ($m_{it} - b_{it}$) and its components: total error ($m_{it} - v(\theta_{it};\ \alpha_j)$), firm-specific error ($m_{it} - v(\theta_{it};\ \alpha_{jt})$), sector error ($v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$), and value-to-book ($v(\theta_{it};\ \alpha_j) - b_{it}$) for the period July 1975 – June 2013. See Appendix A for detailed definitions. Following Asparouhova, Bessembinder, and Kalcheva (2013), two portfolio weighting schemes are used. Panel A shows the performance of prior period gross return weighted (RW) hedge portfolio strategies. Panel B shows the performance of value-weighted (VW) hedge portfolio strategies portfolios. The series correspond to monthly log of one plus cumulative buy-and-hold return of the long-short dollar neutral position in the bottom/top decile of non-financial firms sorted as of June 30 using NYSE breakpoints rebalanced annually.

TABLE 1

Sample formation and descriptive statistics

Panel A: Data selection

	Firm-years	Firms
Matched Compustat/CRSP for the period 1970 - 2011	224,614	21,802
less stocks other than NYSE, AMEX or Nasdaq stocks	*-5,844*	*-655*
Stocks listed on NYSE, AMEX or Nasdaq	218,770	21,147
less stocks other than ordinary common stocks	*-22,024*	*-2,353*
Ordinary common stocks listed on NYSE, AMEX or Nasdaq	196,746	18,794
less financial firms	*-32,892*	*-3,053*
Non-financial firms with ordinary common stocks listed on NYSE, AMEX or Nasdaq	163,854	15,741
less stocks with market value of equity below $10 million on June 30	*-28,207*	*-1,896*
Sample after excluding microcap stocks	135,647	13,845
less observations with missing b, m, ni, LEV, and ROE	*-37,969*	*-2,684*
Sample with non-missing *b, m, ni, LEV* and *ROE*	125,885	13,057
less observations with BP outside [0.01, 100], LEV outside [0, 1], ROE outside [-1, 1]	*-5,327*	*-527*
Final sample	**120,558**	**12,530**

Panel B: Industry composition

FF code	Industry	Firm-years	% of obs.
1	Consumer Non-Durables	10,061	8.35
2	Consumer Durables	4,333	3.59
3	Manufacturing	19,774	16.40
4	Energy	5,776	4.79
5	Chemicals and Allied Products	3,919	3.25
6	Business Equipment	22,407	18.59
7	Telephone and TV Transmission	2,997	2.49
8	Utilities	6,583	5.46
9	Wholesale	16,193	13.43
10	Medical	11,129	9.23
12	Everything else (except finance)	17,386	14.42
Total		**120,558**	**100.00**

Panel C: Descriptive statistics

	N	Mean	St. Dev	1%	5%	25%	Median	75%	95%	99%
ME	120,558	1,736	10,717	10.665	13.597	39.192	139.4	632.0	5,612	28,367
BE	120,558	735.9	3,921	2.268	6.58	26.73	83.3	329.5	2,574	11,705
NI	120,558	76.01	715.4	-222	-31.346	0.466	5.323	28.88	296.816	1,513.4
ROE	120,558	0.074	0.245	-0.800	-0.428	0.017	0.108	0.184	0.389	0.704
LEV	120,558	0.223	0.181	0.000	0.000	0.055	0.208	0.349	0.548	0.694
m	120,558	5.189	1.891	2.367	2.610	3.668	4.937	6.449	8.633	10.253
b	120,558	4.606	1.845	0.819	1.883	3.286	4.422	5.798	7.853	9.368
ni^+	120,558	2.431	1.989	-2.146	-0.587	1.078	2.305	3.710	5.850	7.435
$I_{<0}$	120,558	0.222	0.415	0	0	0	0	0	1	1

This table reports sample formation steps, sample industry composition and sample descriptive statistics. Panel A details the sample selection criteria leading to a final sample of 120,558 firm-year observations for the period 1970-2011 that forms the basis of the valuation model estimation. Panel B reports industry composition of this sample using the Fama-French 12 industries classification (financials excluded). Panel C reports the descriptive statistics of the main variables. *ME* is market value of equity as of June 30 (in US$ mil.). *BE* is book value of common equity (in US$ mil.). *NI* is net income (in US$ mil.). $I_{<0}$ is an indicator variable taking the value of one when net income is negative and zero otherwise. *ROE* is return on equity defined as net income divided by beginning of period book value of common equity, LEV is book leverage defined as long-term debt plus debt in short-term liabilities divided by total assets. Lowercase letters are used for variables expressed in natural logs: *m* is natural logarithm of *ME*, *b* is natural logarithm of *BE*, and ni^{+} is natural logarithm of the absolute value of *NI*.

TABLE 2

Market-to-book decomposition

Panel A: Valuation model: $m_{it} = \alpha_{0jt} + \alpha_{1jt}b_{it} + \alpha_{2jt}ni^{+}_{it} + \alpha_{3jt}I_{(<0)}(ni^{+}_{it}) + \alpha_{4jt}LEV_{it} + \varepsilon_t$

	Fama-French 12 Industry Classification										
	1	2	3	4	5	6	7	8	9	10	12
α_0	1.493	1.622	1.354	1.613	1.814	1.816	1.744	1.294	1.725	2.251	1.863
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α_1	0.554	0.558	0.628	(0.671	0.512	0.602	0.606	0.585	0.522	0.549	0.556
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α_2	0.455	0.391	0.346	0.225	0.469	0.356	0.296	0.371	0.455	0.385	0.348
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
α_3	-0.246	-0.158	-0.174	-0.190	-0.181	-0.247	-0.118	-0.051	-0.289	-0.289	-0.201
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.052)	(0.000)	(0.000)	(0.000)
α_4	-0.246	-0.234	-0.221	0.038	-0.356	-0.273	0.255	-0.137	-0.533	-0.484	-0.434
	(0.000)	(0.025)	(0.001)	(0.588)	(0.010)	(0.000)	(0.002)	(0.190)	(0.000)	(0.000)	(0.000)
R^2	0.871	0.870	0.869	0.901	0.900	0.824	0.876	0.956	0.843	0.847	0.803

Panel B: Decomposition output

	N	Mean	St. Dev	1%	5%	10%	25%	Median	75%	90%	95%	99%
$m_{it} – b_{it}$	113,663	0.604	0.856	-3.566	-1.209	-0.649	0.025	0.534	1.117	2.105	2.967	4.592
$m_{it} – v(\theta_{it}; \alpha_j)$	113,663	0.021	0.698	-4.157	-1.661	-1.063	-0.410	-0.003	0.421	1.210	1.899	4.921
$m_{it} – v(\theta_{it}; \alpha_{jt})$	113,663	0.000	0.663	-4.131	-1.565	-1.027	-0.413	-0.027	0.376	1.143	1.809	4.361
$v(\theta_{it}; \alpha_{jt}) – v(\theta_{it}; \alpha_j)$	113,663	0.021	0.219	-1.894	-0.566	-0.326	-0.096	0.021	0.137	0.379	0.604	2.050
$v(\theta_{it}; \alpha_j) – b_{it}$	113,663	0.583	0.532	-2.951	-0.840	-0.291	0.243	0.630	0.935	1.377	1.747	3.411

This table presents details of the market-to-book decomposition. Panel A reports the estimation results of the valuation model (Eq. 4) estimated on a sample of 120,558 firm-year observations over the period 1970-2011. Cross-sectional regressions are run for each Fama-French 12 industry every year (industry codes are reported across the top). The reported coefficients are time-series averages of the estimated coefficients. Fama-MacBeth *p*-values are reported in parentheses. Time-series averages of R^2s for each industry are also reported. Panel B reports descriptive statistics for log market-to-book ($m_{it} – b_{it}$) and its components: total error ($m_{it} – v(\theta_{it}; \alpha_j)$), firm-specific error ($m_{it} – v(\theta_{it}; \alpha_{jt})$), sector error ($v(\theta_{it}; \alpha_{jt}) – v(\theta_{it}; \alpha_j)$), and value-to-book ($v(\theta_{it}; \alpha_j) – b_{it}$) for a sample of 113,663 firm-year observations over the period 1975-2011. Subscripts *i*, *j*, and *t* denote firm, industry, and year, respectively. See Appendix A for detailed definitions.

TABLE 3

Portfolio sorts on log market-to-book and its components

Panel A: RW portfolio returns

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it}; \alpha_j)$	$m_{it} - v(\theta_{it}; \alpha_{jt})$	$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$	$v(\theta_{it}; \alpha_j) - b_{it}$
Low	1.522	1.496	1.554	1.158	1.220
2	1.533	1.455	1.415	1.295	1.308
3	1.399	1.418	1.350	1.253	1.156
4	1.344	1.317	1.321	1.328	1.258
5	1.254	1.269	1.310	1.286	1.265
6	1.302	1.194	1.285	1.320	1.276
7	1.261	1.103	1.122	1.230	1.316
8	1.189	1.129	1.087	1.222	1.263
9	1.084	0.948	0.982	1.212	1.257
High	0.769	0.743	0.701	1.043	1.104
Low - High	0.754	0.754	0.852	0.115	0.116
t-stat	3.660	4.370	5.554	0.569	0.625
p-value	0.000	0.000	0.000	0.570	0.532
Sharpe Ratio (annualized)	0.594	0.709	0.901	0.092	0.101
N	456	456	456	456	456

Panel B: VW portfolio returns

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it}; \alpha_j)$	$m_{it} - v(\theta_{it}; \alpha_{jt})$	$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$	$v(\theta_{it}; \alpha_j) - b_{it}$
Low	1.494	1.333	1.285	1.057	1.065
2	1.221	1.329	1.109	1.081	1.033
3	1.186	1.273	1.308	1.159	0.914
4	0.954	1.141	1.235	1.129	0.928
5	1.157	1.153	1.288	0.904	1.098
6	1.122	1.014	0.969	0.966	1.070
7	1.043	1.068	1.013	1.069	1.070
8	1.092	1.016	0.965	1.011	1.020
9	0.983	0.863	0.999	1.049	1.120
High	0.907	0.900	0.873	1.018	0.958
Low - High	0.588	0.433	0.411	0.039	0.107
t-stat	2.773	2.215	2.406	0.195	0.627
p-value	0.006	0.027	0.017	0.846	0.531
Sharpe Ratio (annualized)	0.450	0.359	0.390	0.032	0.102
N	456	456	456	456	456

This table presents average monthly returns of decile portfolios sorted on log market-to-book ($m_{it} - b_{it}$), total error ($m_{it} - v(\theta_{it}; \alpha_j)$), firm-specific error ($m_{it} - v(\theta_{it}; \alpha_{jt})$), sector error ($v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$), and value-to-book ($v(\theta_{it}; \alpha_j) - b_{it}$) over the period Jul 1975 – Jun 2013. Following Asparouhova, Bessembinder, and Kalcheva (2013), two portfolio weighting schemes are used. In Panel A, portfolio returns are prior period gross return weighted (RW). In Panel B, portfolio returns are value-weighted (VW). Portfolios are formed every June 30 using NYSE breakpoints and rebalanced annually. Long/short hedge portfolio returns (Low – High) and the associated *t*-statistics, *p*-values, and annualized Sharpe ratios are also shown. See Appendix A for detailed definitions.

TABLE 4
Fama-MacBeth regressions of firm-level returns on log market-to-book and its components

	1	2	3	4	5	6
Intercept	1.369	1.229	1.162	3.080	2.832	2.766
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$m_{it} - b_{it}$	-0.292			-0.266		
	(0.000)			(0.000)		
First decomposition						
$m_{it} - v(\theta_{it}; \alpha_j)$		-0.357			-0.382	
		(0.000)			(0.000)	
$v(\theta_{it}; \alpha_j) - b_{it}$		-0.111			-0.055	
		(0.374)			(0.473)	
Comprehensive decomposition						
$m_{it} - v(\theta_{it}; \alpha_{jt})$			-0.375			-0.394
			(0.000)			(0.000)
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$			-0.127			-0.374
			(0.720)			(0.161)
$v(\theta_{it}; \alpha_j) - b_{it}$			-0.041			-0.023
			(0.737)			(0.778)
Controls						
m				-0.256	-0.234	-0.230
				(0.000)	(0.000)	(0.000)
β^{+}_{post}				0.084	0.092	0.094
				(0.398)	(0.357)	(0.345)
β^{-}_{post}				0.834	0.827	0.828
				(0.000)	(0.000)	(0.000)
$IVol_{post}$				-42.519	-42.706	-42.178
				(0.000)	(0.000)	(0.000)
Illiquidity				0.010	0.010	0.010
				(0.000)	(0.000)	(0.000)
$Ret^{-2\text{-}12}$				0.383	0.401	0.395
				(0.001)	(0.000)	(0.000)
Ret^{-1}				-0.051	-0.051	-0.052
				(0.000)	(0.000)	(0.000)
OP				0.585	0.560	0.591
				(0.000)	(0.000)	(0.000)
Inv				-0.720	-0.697	-0.685
				(0.000)	(0.000)	(0.000)
Adj. R^2	0.008	0.011	0.016	0.078	0.079	0.081
N	456	456	456	456	456	456

This table reports estimation results of Fama-MacBeth regressions of monthly firm-level stock returns on log market-to-book, its components, and control variables over the period Jul 1975 – Jun 2013. Following Asparouhova, Bessembinder, and Kalcheva (2010), regressions are weighted by prior period gross returns (RW). Reported R^2s are cross-sectional means of monthly adjusted R^2s. See Appendix A for detailed definitions of all variables.

TABLE 5

Cash flow risk

Panel A: Campbell and Vuoltenaaho (2004) cash flow beta (N=456 months)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it}; \alpha_j)$	$m_{it} - v(\theta_{it}; \alpha_{jt})$	$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$	$v(\theta_{it}; \alpha_j) - b_{it}$
Low	0.353	0.329	0.324	0.277	0.309
2	0.262	0.262	0.263	0.246	0.266
3	0.249	0.241	0.244	0.239	0.235
4	0.248	0.230	0.241	0.245	0.249
5	0.233	0.228	0.221	0.227	0.254
6	0.239	0.228	0.216	0.224	0.247
7	0.220	0.221	0.228	0.229	0.239
8	0.214	0.222	0.225	0.242	0.226
9	0.210	0.216	0.228	0.229	0.210
High	0.200	0.206	0.206	0.229	0.223
Low - High	0.153	0.123	0.117	0.048	0.085
t-stat	2.991	3.071	3.001	1.195	2.153
p-value	0.003	0.002	0.003	0.233	0.032

Panel B: Da and Warachka (2009) analysts' earnings forecasts beta (N=378 months)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it}; \alpha_j)$	$m_{it} - v(\theta_{it}; \alpha_{jt})$	$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$	$v(\theta_{it}; \alpha_j) - b_{it}$
Low	1.146	1.088	1.129	1.063	1.233
2	1.077	1.045	1.087	1.047	0.956
3	1.077	0.964	1.038	0.867	0.997
4	1.037	1.005	1.014	0.987	1.086
5	1.003	0.998	0.954	1.013	0.987
6	1.017	1.024	0.980	0.953	1.008
7	0.997	0.991	0.975	0.940	0.903
8	1.026	0.944	1.081	0.971	0.871
9	0.877	0.952	0.922	0.857	0.967
High	0.904	1.185	1.067	1.255	0.921
Low - High	0.242	-0.097	0.063	-0.192	0.312
t-stat	2.746	-0.582	0.818	-1.492	3.431
p-value	0.006	0.561	0.414	0.136	0.001

Panel C: Cash flow beta using earnings realizations (N=38 years)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it}; \alpha_j)$	$m_{it} - v(\theta_{it}; \alpha_{jt})$	$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$	$v(\theta_{it}; \alpha_j) - b_{it}$
Low	1.027	1.125	1.023	0.995	1.527
2	1.044	0.907	0.943	1.380	1.053
3	1.079	0.849	0.836	0.567	0.962
4	1.076	0.737	0.814	0.656	1.307
5	1.313	0.661	0.677	0.689	1.518
6	0.867	0.714	0.743	0.726	0.777
7	1.111	0.815	0.932	0.677	0.657
8	0.959	1.136	0.931	0.808	0.924
9	0.776	0.873	0.865	1.000	0.560
High	0.648	1.587	1.758	1.202	0.552
Low - High	0.378	-0.462	-0.735	-0.208	0.975
t-stat	0.683	-1.149	-2.818	-0.330	3.040
p-value	0.499	0.258	0.008	0.743	0.004

This table presents exposures of returns and cashflows of portfolios sorted on log market-to-book and its components to aggregate cashflow shocks. Panel A reports the sensitivity (beta) of monthly portfolio returns to market-level cashflow shocks as in Campbell and Vuoltenaaho (2004). Cashflow shocks are obtained from a VAR-based decomposition of the market return estimated over the period Jan 1929 – Jun 2013. Portfolio returns are prior period gross return weighted (RW). Sample period is Jul 1975 – Jun 2013. Panel B reports the sensitivity (beta) of monthly portfolio-level cashflow news to market-level cashflow news as in Da and Warachka (2009). Cashflow news are computed as revisions in the infinite sum of discounted earnings forecasted by analysts. Sample period is Jan 1982 – June 2013. Panel C reports the sensitivity (beta) of annual portfolio-level cashflow news to market-level cashflows news where cashflow news are obtained as revisions in the sum of discounted sum of portfolio ROEs over a 5-year horizon. Sample period is 1975 – 2012. Portfolios are formed every June 30 using NYSE breakpoints and rebalanced annually. See Appendix A for detailed definitions. *t*-statistics and the associated *p*-values are based on Newey-West standard errors (lag of 5).

TABLE 6

Long-run consumption risk

Panel A: Ultimate consumption risk in returns (Parker and Julliard (2005)) (N=152 quarters)

	$m_{it} – b_{it}$	$m_{it} – v(\theta_{it}; \alpha_j)$	$m_{it} – v(\theta_{it}; \alpha_{jt})$	$v(\theta_{it}; \alpha_{jt}) – v(\theta_{it}; \alpha_j)$	$v(\theta_{it}; \alpha_j) – b_{it}$
Low	0.707	0.599	0.586	0.266	0.400
2	0.531	0.455	0.449	0.428	0.369
3	0.463	0.385	0.376	0.384	0.341
4	0.399	0.370	0.375	0.386	0.397
5	0.372	0.292	0.227	0.244	0.416
6	0.304	0.257	0.255	0.295	0.304
7	0.224	0.229	0.241	0.339	0.403
8	0.230	0.112	0.188	0.326	0.370
9	0.152	0.150	0.129	0.292	0.299
High	0.019	0.041	0.059	0.259	0.131
Low - High	0.694	0.557	0.532	-0.017	0.277
t-stat	3.072	3.100	3.173	-0.068	1.736
p-value	0.003	0.002	0.002	0.946	0.085

Panel B: Consumption risk in cahflows (dividends) (Bansal, Dittmar and Lundblad (2005)) (N=148 quarters)

	$m_{it} – b_{it}$	$m_{it} – v(\theta_{it}; \alpha_j)$	$m_{it} – v(\theta_{it}; \alpha_{jt})$	$v(\theta_{it}; \alpha_{jt}) – v(\theta_{it}; \alpha_j)$	$v(\theta_{it}; \alpha_j) – b_{it}$
Low	-0.108	1.769	1.212	-5.618	0.072
2	-3.025	-3.532	0.455	-6.310	2.219
3	0.595	-2.013	-1.600	-4.533	-3.385
4	0.669	1.177	0.718	-1.684	-5.751
5	1.053	1.747	-1.020	2.280	-4.009
6	0.760	1.249	0.232	4.459	0.820
7	-1.337	-0.031	-0.751	4.941	0.131
8	-3.043	-0.526	-2.918	7.143	2.445
9	-0.556	-1.140	-1.406	0.777	-1.700
High	-1.553	-4.706	-3.444	-0.259	1.131
Low - High	1.445	6.475	4.656	-5.358	-1.060
t-stat	0.222	1.106	0.877	-0.536	-0.218
p-value	0.825	0.271	0.382	0.592	0.828

Panel C: Ultimate consumption risk in cashflows (dividends) (N=148 quarters)

	$m_{it} – b_{it}$	$m_{it} – v(\theta_{it}; \alpha_j)$	$m_{it} – v(\theta_{it}; \alpha_{jt})$	$v(\theta_{it}; \alpha_{jt}) – v(\theta_{it}; \alpha_j)$	$v(\theta_{it}; \alpha_j) – b_{it}$
Low	0.068	-0.202	-0.075	-0.609	-0.230
2	-0.137	0.045	-0.060	-0.406	-0.333
3	0.004	-0.278	-0.401	-0.192	-0.214
4	-0.255	-0.360	-0.363	0.037	0.169
5	-0.241	-0.283	-0.094	-0.292	0.049
6	-0.314	-0.337	-0.390	-0.137	-0.402
7	-0.353	-0.175	-0.159	-0.223	-0.067
8	-0.146	-0.389	-0.320	-0.349	-0.164
9	-0.556	-0.192	-0.191	0.092	-0.216
High	-0.155	0.126	-0.078	0.277	-0.669
Low - High	0.223	-0.327	0.003	-0.885	0.439
t-stat	0.502	-0.532	0.007	-0.702	1.245
p-value	0.616	0.595	0.994	0.484	0.215

Panel D: Ultimate consumption risk in cashflows (analysts' earnings forecasts) (N=128 quarters)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it};\ \alpha_j)$	$m_{it} - v(\theta_{it};\ \alpha_{jt})$	$v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$	$v(\theta_{it};\ \alpha_j) - b_{it}$
Low	0.196	0.186	0.182	0.066	0.217
2	0.144	0.117	0.178	0.065	-0.015
3	0.172	0.159	0.112	0.059	0.116
4	0.169	-0.036	0.074	0.124	0.121
5	0.038	0.234	0.123	0.155	0.163
6	0.071	0.072	0.045	0.078	0.211
7	0.065	0.118	0.054	0.044	0.176
8	0.036	0.013	0.128	0.082	0.020
9	0.086	0.084	0.096	0.181	0.039
High	0.060	0.252	0.062	0.365	-0.082
Low - High	0.135	-0.066	0.120	-0.299	0.299
t-stat	0.846	-0.294	0.824	-1.578	2.788
p-value	0.399	0.769	0.412	0.117	0.006

Panel E: Ultimate consumption risk in cashflows (earnings realizations) (N=38 years)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it};\ \alpha_j)$	$m_{it} - v(\theta_{it};\ \alpha_{jt})$	$v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$	$v(\theta_{it};\ \alpha_j) - b_{it}$
Low	-0.058	-0.058	0.064	-0.254	0.354
2	0.001	-0.133	0.138	0.254	0.289
3	0.202	-0.090	0.041	-0.096	0.226
4	0.290	0.045	0.138	0.106	0.638
5	0.272	0.199	-0.016	0.057	0.266
6	0.441	0.033	0.158	0.257	0.316
7	0.465	0.341	0.355	0.138	0.181
8	0.420	0.382	0.374	0.386	0.179
9	0.382	0.422	0.235	0.165	-0.059
High	-0.121	0.321	0.242	0.666	-0.112
Low - High	0.063	-0.378	-0.178	-0.920	0.466
t-stat	0.245	-1.273	-0.666	-1.628	1.742
p-value	0.808	0.211	0.510	0.112	0.090

This table presents exposures of returns and cashflows of portfolios sorted on log market-to-book and its components to long-run consumption. Panel A reports the sensitivity (beta) of quarterly portfolio returns to ultimate consumption growth as in Parker and Julliard (2005). Ultimate consumption growth is the log growth rate in real per capita consumption of non-durable goods from quarter t to quarter t+11. Quarterly portfolio returns are obtained by cumulating monthly returns and are converted to real using the PCE deflator. Portfolio returns are prior period gross return weighted (RW). Sample period is 1975:Q3 – 2013:Q2. Panel B reports the sensitivity (beta) of portfolio-level dividends to long-run past consumption growth as in Bansal, Dittmar and Lundblad (2005). Quarterly portfolio dividends are extracted from CRSP data using monthly returns with and without dividends (prior period gross return weighted (RW)) and aggregated to quarterly. The resulting series is converted to real using the PCE deflator, seasonally-adjusted by taking a 4-quarter moving average, and log growth rates are taken. Long-run past consumption growth is an 8-quarter moving average of log quarterly growth rates in real per capita consumption of non-durables and services over t-1 to t-8. Sample period is 1976:Q3 – 2013:Q2. Panel C reports the sensitivity (beta) of portfolio-level dividends from Panel B to ultimate consumption growth from Panel A. Panel D reports the sensitivity (beta) of quarterly portfolio-level cashflow news using revisions in the sum of discounted analysts' earnings forecasts to ultimate consumption growth from Panel A. Monthly revisions are aggregated to quarterly. Sample period is 1982:Q3 – 2013:Q2. Panel E reports the sensitivity (beta) of annual portfolio-level cashflow news obtained as revisions in the sum of discounted sum of portfolio ROEs over a 5-year horizon to ultimate consumption growth from Panel A. Q4 ultimate consumption growth is used to match the annual frequency of the cashflow news series. Sample period is 1975 –2012. Portfolios are formed every June 30 using NYSE breakpoints and rebalanced annually. See Appendix A for detailed definitions. t-statistics and the associated p-values are based on Newey-West standard errors (lag of 5).

TABLE 7

Exposure to investment-specific technology shocks (Kogan and Papanikolau (2014)) (N=456 months)

	$m_{it} – b_{it}$	$m_{it} – v(\theta_{it}; \alpha_j)$	$m_{it} – v(\theta_{it}; \alpha_{jt})$	$v(\theta_{it}; \alpha_{jt}) – v(\theta_{it}; \alpha_j)$	$v(\theta_{it}; \alpha_j) – b_{it}$
Low	0.747	0.847	0.885	0.816	0.602
2	0.624	0.746	0.716	0.769	0.477
3	0.577	0.663	0.665	0.675	0.524
4	0.593	0.632	0.655	0.614	0.600
5	0.642	0.607	0.611	0.594	0.655
6	0.679	0.636	0.642	0.671	0.689
7	0.740	0.639	0.668	0.636	0.654
8	0.768	0.699	0.716	0.588	0.744
9	0.858	0.800	0.794	0.636	0.884
High	1.016	0.987	0.980	0.875	1.054
Low - High	-0.269	-0.140	-0.095	-0.060	-0.452
t-stat	-2.884	-1.765	-1.858	-0.527	-3.592
p-value	0.004	0.078	0.064	0.599	0.000

This table presents the sensitivity (beta) of portfolio returns to investment-specific technology shocks of Kogan and Papanikolau (2014). The sensitivities are estimated as portfolio return betas with respect to a factor mimicking portfolio long investment goods producers and short consumer goods producers (IMC factor). Portfolio returns are prior period gross return weighted (RW), the IMC factor return is value-weighted (VW). Portfolios are formed every June 30 using NYSE breakpoints and rebalanced annually. Betas are not estimated for investment goods producers and service firms, and the portfolios are sorted after these firms are excluded. Industry classifications are from Gomes, Kogan, and Yogo (2009). Sample period is Jul 1975 – Jun 2013. See Appendix A for detailed definitions. *t*-statistics and the associated *p*-values are based on Newey-West standard errors (lag of 5).

TABLE 8

Operating leverage

Panel A: Firm age (number of years on CRSP)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it}; \alpha_j)$	$m_{it} - v(\theta_{it}; \alpha_{jt})$	$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$	$v(\theta_{it}; \alpha_j) - b_{it}$
Low	17.905	14.197	14.136	17.215	22.915
2	19.140	15.834	16.020	17.858	23.984
3	19.843	17.519	17.166	17.376	21.877
4	19.422	18.224	18.634	16.695	19.785
5	18.354	18.918	19.032	16.838	18.132
6	17.671	19.011	19.091	16.811	17.509
7	16.716	18.341	18.233	17.693	16.313
8	15.570	17.378	17.260	18.823	15.127
9	14.570	16.278	16.024	19.510	14.064
High	11.686	13.514	13.104	19.659	12.022
Low - High	6.220	0.682	1.031	-2.444	10.893
t-stat	3.344	1.031	3.943	-0.828	4.528
p-value	0.002	0.309	0.000	0.413	0.000

Panel B: Book **l**everage

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it}; \alpha_j)$	$m_{it} - v(\theta_{it}; \alpha_{jt})$	$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$	$v(\theta_{it}; \alpha_j) - b_{it}$
Low	0.273	0.217	0.219	0.233	0.310
2	0.251	0.215	0.214	0.219	0.303
3	0.247	0.221	0.223	0.218	0.298
4	0.241	0.226	0.230	0.217	0.274
5	0.234	0.231	0.231	0.213	0.244
6	0.223	0.229	0.235	0.214	0.223
7	0.210	0.227	0.226	0.219	0.206
8	0.201	0.219	0.219	0.235	0.189
9	0.190	0.216	0.211	0.247	0.174
High	0.188	0.227	0.219	0.273	0.172
Low - High	0.084	-0.010	0.000	-0.040	0.138
t-stat	15.299	-1.926	-0.278	-1.950	12.128
p-value	0.000	0.062	0.783	0.059	0.000

Panel C: Sensitivity to idiosyncratic volatility (Ai and Kiku (2016))

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it}; \alpha_j)$	$m_{it} - v(\theta_{it}; \alpha_{jt})$	$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$	$v(\theta_{it}; \alpha_j) - b_{it}$
Low	0.019	0.026	0.027	0.022	0.017
2	0.020	0.025	0.025	0.021	0.015
3	0.021	0.022	0.024	0.021	0.015
4	0.021	0.021	0.021	0.021	0.019
5	0.021	0.020	0.019	0.021	0.020
6	0.023	0.019	0.020	0.022	0.023
7	0.024	0.021	0.022	0.022	0.024
8	0.024	0.022	0.022	0.022	0.026
9	0.026	0.025	0.024	0.023	0.027
High	0.033	0.030	0.030	0.026	0.033
Low - High	-0.014	-0.004	-0.003	-0.004	-0.015
t-stat	-3.191	-1.008	-0.751	-0.704	-4.103
p-value	0.003	0.320	0.457	0.486	0.000

Panel D: Fixed asset tangibility

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it}; \alpha_j)$	$m_{it} - v(\theta_{it}; \alpha_{jt})$	$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$	$v(\theta_{it}; \alpha_j) - b_{it}$
Low	0.361	0.296	0.294	0.344	0.405
2	0.369	0.313	0.310	0.334	0.454
3	0.380	0.332	0.334	0.324	0.452
4	0.373	0.352	0.357	0.323	0.415
5	0.359	0.363	0.369	0.327	0.368
6	0.336	0.358	0.365	0.333	0.333
7	0.314	0.352	0.350	0.342	0.312
8	0.298	0.328	0.332	0.348	0.288
9	0.282	0.317	0.309	0.357	0.264
High	0.263	0.298	0.294	0.362	0.240
Low - High	0.097	-0.002	0.000	-0.018	0.165
t-stat	7.752	-0.232	-0.055	-0.538	9.964
p-value	0.000	0.818	0.956	0.594	0.000

This table presents characteristics pertaining to operating inflexibility of portfolios sorted on log market-to-book and its components. Panel A reports the average age of firms across portfolios sorted on log market-to-book and its components. Firm age is the number of years between portfolio formation date and the first date the stock appears in CRSP. Panel B reports the average book leverage (*LEV*) of firms across portfolios sorted on log market-to-book and its components. Panel C reports the average firm-level return sensitivity (beta) to innovations in idiosyncratic volatility following Ai and Kiku (2016) across portfolios sorted on log market-to-book and its components. Betas and innovations for each firm are obtained using prior 5 years of monthly data. Panel D reports the average fixed asset tangibility (property, plant, and equipment divided by total assets) of firms across portfolios sorted on log market-to-book and its components. In all panels, time-series averages of portfolio means across 38 portfolio formations (1975-2012) are reported. Portfolios are formed every June 30 using NYSE breakpoints and rebalanced annually. See Appendix A for detailed definitions. *t*-statistics and the associated *p*-values are based on Newey-West standard errors (lag of 5).

TABLE 9

Duration

Panel A: Dechow, Sloan, and Soliman (2004) equity duration implied by *v*

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it};\ \alpha_j)$	$m_{it} - v(\theta_{it};\ \alpha_{jt})$	$v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$	$v(\theta_{it};\ \alpha_j) - b_{it}$
Low	15.498	16.686	16.616	16.640	13.193
2	15.442	16.197	16.173	16.035	14.777
3	15.524	15.976	15.987	15.899	15.235
4	15.586	15.821	15.786	15.839	15.597
5	15.774	15.751	15.696	15.819	15.803
6	15.890	15.716	15.727	15.770	15.957
7	16.056	15.757	15.817	15.751	16.075
8	16.211	15.852	15.879	15.687	16.243
9	16.418	15.900	15.983	15.671	16.528
High	17.062	16.099	16.241	15.696	17.326
Low - High	-1.564	0.587	0.375	0.944	-4.133
t-stat	-4.183	4.715	4.977	2.646	-8.540
p-value	0.000	0.000	0.000	0.012	0.000

Panel B: Modified Da (2009) portfolio-level cashflow duration

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it};\ \alpha_j)$	$m_{it} - v(\theta_{it};\ \alpha_{jt})$	$v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$	$v(\theta_{it};\ \alpha_j) - b_{it}$
Low	0.403	0.291	0.307	0.243	0.137
2	0.049	0.081	0.165	0.233	0.034
3	-0.068	-0.086	0.062	0.399	0.180
4	0.129	0.044	0.032	0.256	0.317
5	0.089	0.249	0.094	0.198	0.261
6	0.197	0.168	0.110	0.227	0.347
7	0.342	0.208	0.325	0.328	0.417
8	0.397	0.382	0.324	0.267	0.403
9	0.466	0.510	0.513	0.357	0.613
High	0.709	0.428	0.441	0.275	0.552
Low - High	-0.306	-0.137	-0.135	-0.032	-0.415
t-stat	-1.843	-1.450	-1.472	-0.254	-3.378
P-value	0.074	0.156	0.150	0.801	0.002

Panel C: Chen (2017) buy-and-hold portfolio dividend growth rates (geometric average of years 1-10)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it};\ \alpha_j)$	$m_{it} - v(\theta_{it};\ \alpha_{jt})$	$v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$	$v(\theta_{it};\ \alpha_j) - b_{it}$
Low	10.074	10.644	10.594	9.657	7.783
2	7.824	9.336	8.711	9.948	6.408
3	9.073	9.470	9.181	8.965	7.495
4	9.259	9.316	9.254	9.942	9.296
5	9.309	8.708	8.694	9.208	9.478
6	10.288	9.254	8.494	9.349	9.756
7	10.281	9.227	9.680	9.079	8.850
8	11.067	10.072	11.431	7.611	9.774
9	12.612	10.500	10.290	8.339	12.480
High	12.456	10.490	10.982	7.828	12.333
Low - High	-2.382	0.154	-0.388	1.829	-4.550
t-stat	-2.730	0.152	-0.322	1.963	-2.299
p-value	0.011	0.880	0.750	0.060	0.029

This table presents duration characteristics of portfolios sorted on log market-to-book and its components. Panel A reports the time-series average of portfolio means of equity duration implied by the estimate of fundamental value *v*. Implied equity duration is computed as in Dechow, Sloan, and Soliman (2004) except that estimate of fundamental value *v* is used instead of market capitalization. Time-series averages are taken across 38 portfolio formations (1975-2012). Panel B reports the time-series average of portfolio-level duration following Da (2009) with two modifications: first year (look-back) growth rate is skipped, and year 7 growth rate is used for the terminal value instead of the average of years 1-7. Time-series averages are taken across 36 portfolio formations (1975-2010). Panel C reports the time-series average of buy-and-hold portfolio dividend growth rates following Chen (2017). For each of the ten years following portfolio formation, annual dividends are extracted from monthly CRSP data using returns with and without dividends (added up from July to June). Portfolio returns are prior period gross return weighted (RW). Geometric average growth rates in dividends from year 1 to year 10 is then computed. Time-series averages are taken across 33 portfolio formations (1975-2007). Portfolios are formed every June 30 using NYSE breakpoints and rebalanced annually. See Appendix A for detailed definitions. *t*-statistics and *p*-values are based on Newey-West adjusted standard errors (lag of 5).

TABLE 10

Analysts' risk ratings

	1	2	3	4	5	6
$m_{it} - b_{it}$	-0.287			-0.195		
	(0.008)			(0.089)		
First decomposition						
$m_{it} - v(\theta_{it}; \alpha_j)$		-0.046			-0.099	
		(0.680)			(0.461)	
$v(\theta_{it}; \alpha_j) - b_{it}$		-0.739			-0.371	
		(0.000)			(0.021)	
$m_{it} - v(\theta_{it}; \alpha_{jt})$			-0.070			-0.179
			(0.544)			(0.205)
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$			0.358			1.028
			(0.220)			(0.002)
$v(\theta_{it}; \alpha_j) - b_{it}$			-0.704			-0.285
			(0.000)			(0.080)
m				-0.615	-0.615	-0.596
				(0.000)	(0.000)	(0.000)
β_{pre}				1.097	1.076	1.058
				(0.000)	(0.000)	(0.000)
$Ivol_{pre}$				168.229	166.612	172.706
				(0.000)	(0.000)	(0.000)
Illiquidity				-0.465	-0.450	-0.539
				(0.652)	(0.669)	(0.601)
LEV				0.087	-0.058	-0.087
				(0.872)	(0.911)	(0.868)
R^2	0.011	0.019	0.020	0.296	0.297	0.300
N	2,190	2,190	2,190	2,190	2,190	2,190

The table reports estimation results of pooled ordered logit regressions of analysts' risk ratings on log market-to-book, its components, and control variables. Year fixed effects are included in all regressions. The sample consists of 2,190 stock-year observations covering the period 2003 – 2010. *p*-values in parentheses are based on heteroscedasticity-robust standard errors clustered by firm. See Appendix A for detailed definitions.

TABLE 11

Evidence on expectational errors: excess returns around earnings announcements

	Low	2	3	4	5	6	7	8	9	High	Low-High
Panel A: Post-portfolio formation											
$m_{it} - b_{it}$	0.036	0.021	0.013	0.004	0.003	-0.001	-0.004	-0.013	-0.023	-0.047	0.084
	(0.001)	(0.001)	(0.017)	(0.401)	(0.555)	(0.772)	(0.309)	(0.005)	(0.000)	(0.000)	(0.000)
$m_{it} - v(\theta_{it};\ \alpha_j)$	0.028	0.012	0.010	0.001	0.001	-0.002	-0.013	-0.016	-0.022	-0.048	0.076
	(0.004)	(0.025)	(0.057)	(0.799)	(0.893)	(0.641)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
$m_{it} - v(\theta_{it};\ \alpha_{jt})$	0.028	0.009	0.005	0.005	0.001	-0.002	-0.010	-0.014	-0.020	-0.046	0.074
	(0.005)	(0.131)	(0.322)	(0.343)	(0.746)	(0.721)	(0.005)	(0.003)	(0.000)	(0.000)	(0.000)
$v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$	0.008	0.004	0.001	0.008	0.001	-0.003	-0.008	-0.007	-0.015	-0.023	0.031
	(0.229)	(0.486)	(0.833)	(0.120)	(0.790)	(0.548)	(0.119)	(0.099)	(0.004)	(0.000)	(0.001)
$v(\theta_{it};\ \alpha_j) - b_{it}$	0.007	0.006	0.010	0.003	0.001	-0.002	-0.001	-0.007	-0.007	-0.022	0.029
	(0.230)	(0.141)	(0.060)	(0.530)	(0.762)	(0.688)	(0.861)	(0.153)	(0.190)	(0.003)	(0.000)
Panel B: Pre-portfolio formation											
$m_{it} - b_{it}$	-0.044	-0.018	-0.007	-0.005	0.000	0.006	0.011	0.015	0.020	0.025	-0.069
	(0.000)	(0.000)	(0.179)	(0.293)	(0.915)	(0.231)	(0.017)	(0.011)	(0.003)	(0.001)	(0.000)
$m_{it} - v(\theta_{it};\ \alpha_j)$	-0.044	-0.017	-0.009	0.005	0.003	0.013	0.012	0.017	0.030	0.033	-0.077
	(0.000)	(0.006)	(0.040)	(0.305)	(0.492)	(0.014)	(0.015)	(0.002)	(0.000)	(0.000)	(0.000)
$m_{it} - v(\theta_{it};\ \alpha_{jt})$	-0.043	-0.017	-0.008	0.000	0.006	0.011	0.013	0.017	0.025	0.035	-0.077
	(0.000)	(0.006)	(0.110)	(0.942)	(0.157)	(0.031)	(0.007)	(0.001)	(0.000)	(0.000)	(0.000)
$v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$	-0.015	-0.003	0.005	-0.003	0.007	0.007	0.009	0.009	0.005	0.003	-0.017
	(0.008)	(0.584)	(0.523)	(0.594)	(0.180)	(0.207)	(0.096)	(0.099)	(0.310)	(0.653)	(0.034)
$v(\theta_{it};\ \alpha_j) - b_{it}$	0.005	0.005	0.002	0.002	0.002	0.003	0.008	0.006	-0.001	-0.008	0.012
	(0.406)	(0.235)	(0.664)	(0.718)	(0.670)	(0.550)	(0.132)	(0.259)	(0.910)	(0.288)	(0.107)

The table presents average excess earnings announcement returns across portfolios sorted on log market-to-book and its components. For every firm in the portfolio we add up four excess earnings announcement returns over four quarters following portfolio formation (Panel A) or prior to portfolio formation (Panel B). Excess earnings announcement returns are computed as buy-and-hold abnormal returns in the [-5, +5] event window centered on the quarterly earnings announcement date reported by Compustat. Abnormal returns are calculated using the market model with parameters estimated over the period starting 240 days and ending 41 days prior to the announcement (CRSP value-weighted index is the market return). Portfolios are formed every June 30 using NYSE breakpoints and rebalanced annually. See Appendix A for detailed definitions.

TABLE 12

Limits to arbitrage: short-sale constraints proxied by institutional ownership

Panel A: Double sort with log market-to-book ($m_{it} - b_{it}$)

	Residual Institutional Ownership						
	Low	2	3	4	High	High-Low	*p*-value
$m_{it} - b_{it}$							
Low	1.091	1.383	1.566	1.235	1.485	0.394	0.049
2	1.223	1.188	1.263	1.270	1.297	0.074	0.597
3	0.937	1.148	1.295	1.213	1.265	0.328	0.020
4	0.827	1.054	1.172	1.048	1.273	0.445	0.002
High	0.287	0.863	0.895	0.936	1.042	0.755	0.000
Low - High	0.804	0.520	0.671	0.299	0.443	-0.360	0.125
p-value	0.000	0.009	0.001	0.143	0.065		

Panel B: Double sort with total error ($m_{it} - v(\theta_{it}; \alpha_j)$)

	Residual Institutional Ownership						
	Low	2	3	4	High	High-Low	*p*-value
$m_{it} - v(\theta_{it}; \alpha_j)$							
Low	1.143	1.255	1.455	1.197	1.474	0.331	0.078
2	1.132	1.257	1.310	1.319	1.246	0.114	0.425
3	0.928	1.124	1.168	1.151	1.189	0.261	0.079
4	0.609	1.039	1.192	0.996	1.128	0.519	0.001
High	0.268	0.820	0.873	0.919	1.044	0.776	0.000
Low - High	0.875	0.435	0.583	0.278	0.430	-0.445	0.032
p-value	0.000	0.027	0.001	0.130	0.040		

Panel C: Double sort with firm-specific error ($m_{it} - v(\theta_{it}; \alpha_{jt})$)

	Residual Institutional Ownership						
	Low	2	3	4	High	High-Low	*p*-value
$m_{it} - v(\theta_{it}; \alpha_{jt})$							
Low	1.164	1.218	1.404	1.228	1.478	0.314	0.100
2	1.036	1.234	1.332	1.258	1.214	0.178	0.198
3	1.044	1.210	1.307	1.086	1.305	0.262	0.100
4	0.678	0.944	1.086	1.073	1.071	0.394	0.008
High	0.243	0.854	0.896	0.948	1.057	0.814	0.000
Low - High	0.921	0.364	0.508	0.279	0.421	-0.500	0.014
p-value	0.000	0.041	0.002	0.099	0.031		

Panel D: Double sort with sector error ($v(\theta_{it}; \alpha_{jt})_t - v(\theta_{it}; \alpha_j)$)

	Residual Institutional Ownership						
	Low	2	3	4	High	High-Low	*p*-value
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$							
Low	0.842	1.030	1.323	1.147	1.383	0.540	0.002
2	0.850	1.180	1.256	1.205	1.363	0.513	0.000
3	0.888	1.249	1.316	1.254	1.331	0.443	0.001
4	0.823	1.138	1.148	1.153	1.226	0.403	0.004
High	0.664	0.971	1.029	0.892	1.060	0.397	0.014
Low - High	0.179	0.059	0.295	0.255	0.322	0.144	0.495
p-value	0.448	0.782	0.124	0.186	0.088		

TABLE 12 (Continued)

Panel E: Double sort with long-run value-to-book ($v(\theta_{it};\, \alpha_j) - b_{it}$)

	Residual Institutional Ownership						
	Low	2	3	4	High	High-Low	*p*-value
$v(\theta_{it};\, \alpha_j) - b_{it}$							
Low	0.947	1.131	1.281	1.010	1.294	0.347	0.066
2	0.822	1.127	1.286	1.055	1.293	0.471	0.013
3	0.792	1.147	1.152	1.223	1.278	0.486	0.001
4	0.855	1.148	1.213	1.248	1.245	0.390	0.001
High	0.620	0.938	1.144	1.087	1.279	0.658	0.000
Low – High	0.327	0.193	0.137	-0.077	0.015	-0.311	0.166
p-value	0.202	0.293	0.456	0.681	0.938		

This table presents average monthly returns of portfolios independently sorted on log market-to-book (or its components) and residual institutional ownership following Nagel (2003). Residual institutional ownership is as of two quarters prior to portfolio formation date (end of December). Residual institutional ownership is orthogonalized with respect to size and size-squared. See Appendix A for detailed definitions. Portfolio returns are prior period gross return weighted (RW). The time period is Jul 1975 – Jun 2013. Portfolios are formed every June 30 using NYSE breakpoints and rebalanced annually.

TABLE 13

Limits to arbitrage: noise trader risk proxied by idiosyncratic volatility

Panel A: Double sort with market-to-book ($m_{it} - b_{it}$)

	Idiosyncratic Volatility						
	Low	2	3	4	High	High-Low	*p*-value
$m_{it} - b_{it}$							
Low	1.432	1.557	1.372	1.458	1.428	-0.003	0.991
2	1.174	1.313	1.443	1.313	1.381	0.207	0.433
3	1.223	1.259	1.311	1.403	1.246	0.023	0.925
4	1.196	1.206	1.355	1.406	1.101	-0.095	0.703
High	1.188	1.178	1.236	1.152	0.740	-0.449	0.131
Low – High	0.243	0.379	0.136	0.306	0.689	0.446	0.022
p-value	0.063	0.004	0.371	0.058	0.000		

Panel B: Double sort with total error ($m_{it} - v(\theta_{it}; \alpha_j)$)

	Idiosyncratic Volatility						
	Low	2	3	4	High	High-Low	*p*-value
$m_{it} - v(\theta_{it}; \alpha_j)$							
Low	1.383	1.504	1.374	1.455	1.396	0.013	0.958
2	1.309	1.382	1.488	1.466	1.268	-0.041	0.869
3	1.184	1.261	1.380	1.377	1.139	-0.044	0.875
4	1.169	1.172	1.240	1.180	1.070	-0.099	0.706
High	1.089	1.102	1.158	1.127	0.622	-0.467	0.106
Low – High	0.294	0.401	0.216	0.329	0.774	0.480	0.007
p-value	0.034	0.002	0.089	0.018	0.000		

Panel C: Double sort with firm-specific error ($m_{it} - v(\theta_{it}; \alpha_{jt})$)

	Idiosyncratic Volatility						
	Low	2	3	4	High	High-Low	*p*-value
$m_{it} - v(\theta_{it}; \alpha_{jt})$							
Low	1.359	1.447	1.338	1.466	1.469	0.109	0.660
2	1.308	1.377	1.507	1.468	1.201	-0.107	0.685
3	1.201	1.299	1.399	1.365	1.257	0.057	0.840
4	1.195	1.144	1.266	1.160	0.998	-0.198	0.455
High	1.076	1.142	1.148	1.159	0.613	-0.462	0.105
Low - High	0.284	0.305	0.191	0.307	0.855	0.571	0.000
p-value	0.025	0.013	0.121	0.019	0.000		

Panel D: Double sort with sector error ($v(\theta_{it}; \alpha_{jt})_t - v(\theta_{it}; \alpha_j)$)

	Idiosyncratic Volatility						
	Low	2	3	4	High	High-Low	*p*-value
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$							
Low	1.218	1.275	1.341	1.162	1.019	-0.199	0.451
2	1.217	1.371	1.398	1.328	1.123	-0.094	0.706
3	1.166	1.315	1.345	1.462	1.250	0.084	0.727
4	1.218	1.210	1.266	1.304	1.156	-0.062	0.817
High	1.249	1.231	1.264	1.293	1.003	-0.245	0.395
Low – High	-0.030	0.044	0.077	-0.131	0.016	0.046	0.819
p-value	0.822	0.708	0.589	0.396	0.932		

TABLE 13 (Continued)

Panel E: Double sort with value to book ($v(\theta_{it};\ \alpha_j) - b_{it}$)

	Idiosyncratic Volatility						
	Low	2	3	4	High	High-Low	*p*-value
$v(\theta_{it};\ \alpha_j) - b_{it}$							
Low	1.185	1.251	1.239	1.203	1.223	0.038	0.895
2	1.111	1.214	1.361	1.289	1.173	0.062	0.812
3	1.332	1.345	1.338	1.395	1.200	-0.132	0.573
4	1.277	1.309	1.313	1.385	1.149	-0.129	0.572
High	1.281	1.299	1.377	1.322	1.061	-0.220	0.459
Low – High	-0.096	-0.048	-0.138	-0.119	0.162	0.258	0.227
p-value	0.454	0.663	0.264	0.398	0.377		

This table presents average monthly returns of portfolios independently sorted on log market-to-book (or its components) and idiosyncratic return volatility ($IVOL_{pre}$) following Ali, Hwang, and Trombley (2003). Idiosyncratic volatility is calculated as the standard deviation of residuals from a regression of daily stock returns on the CRSP value-weighted market return using 12 months prior to portfolio formation. See Appendix A for detailed definitions. Portfolio returns are prior period gross return weighted (RW). The time period is Jul 1975 – Jun 2013. Portfolios are formed every June 30 using NYSE breakpoints and rebalanced annually.

TABLE 14

Limits to arbitrage: time-series test using hedge funds assets under management

Panel A: Sort on market-to-book ($m_{it} - b_{it}$)

	Arbitrage Capital				
	Low (84 months)	Medium (96 months)	High (84 months)	High-Low	*p*-value
$m_{it} - b_{it}$					
Low	1.206	1.856	1.028	-0.178	0.878
2	1.084	1.759	1.187	0.103	0.910
3	1.216	1.671	0.811	-0.405	0.642
4	1.100	1.464	0.821	-0.279	0.748
5	1.121	1.387	0.666	-0.455	0.599
6	1.172	1.432	0.780	-0.392	0.657
7	1.027	1.386	0.692	-0.334	0.715
8	1.058	1.351	0.647	-0.411	0.656
9	0.644	1.265	0.656	0.012	0.990
High	0.372	1.179	0.456	0.084	0.939
Low – High	0.833	0.677	0.572	-0.262	0.734
p-value	0.127	0.185	0.295		

Panel B: Sort on total error ($m_{it} - v(\theta_{it}; \alpha_j)$)

	Arbitrage Capital				
	Low (84 months)	Medium (96 months)	High (84 months)	High-Low	*p*-value
$m_{it} - v(\theta_{it}; \alpha_j)$					
Low	1.377	1.947	0.980	-0.397	0.728
2	1.157	1.717	0.886	-0.272	0.778
3	1.204	1.601	0.854	-0.350	0.700
4	1.075	1.326	0.773	-0.302	0.723
5	1.221	1.360	0.810	-0.411	0.632
6	0.891	1.385	0.771	-0.120	0.888
7	0.925	1.150	0.646	-0.279	0.737
8	0.802	1.327	0.807	0.004	0.996
9	0.592	1.161	0.557	-0.035	0.972
High	0.167	1.075	0.482	0.315	0.772
Low - High (Raw)	1.209	0.872	0.497	-0.712	0.264
p-value	0.008	0.039	0.270		

TABLE 14 (Continued)

Panel C: Sort on firm-specific error ($m_{it} - v(\theta_{it};\ \alpha_{jt})$)

	Arbitrage Capital				
	Low (84 months)	Medium (96 months)	High (84 months)	High-Low	*p*-value
$m_{it} - v(\theta_{it};\ \alpha_{jt})$					
Low	1.434	1.954	0.943	-0.491	0.665
2	1.228	1.675	0.762	-0.466	0.624
3	1.027	1.413	0.914	-0.112	0.900
4	0.911	1.548	0.796	-0.115	0.896
5	1.078	1.384	0.858	-0.220	0.792
6	1.178	1.465	0.939	-0.239	0.782
7	0.885	1.235	0.621	-0.264	0.762
8	0.679	1.360	0.733	0.053	0.952
9	0.802	1.222	0.610	-0.192	0.843
High	0.097	1.061	0.542	0.445	0.683
Low - High	1.338	0.893	0.401	-0.936	0.105
p-value	0.001	0.020	0.325		

Panel D: Sort on sector error ($v(\theta_{it};\ \alpha_{jt})_t - v(\theta_{it};\ \alpha_j)$)

	Arbitrage Capital				
	Low (84 months)	Medium (96 months)	High (84 months)	High-Low	*p*-value
$v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$					
Low	0.676	1.744	1.269	0.594	0.596
2	1.062	1.568	0.871	-0.191	0.847
3	1.134	1.427	0.824	-0.310	0.735
4	1.274	1.403	0.838	-0.435	0.612
5	1.102	1.259	0.926	-0.176	0.835
6	1.222	1.384	0.799	-0.423	0.639
7	1.240	1.350	0.516	-0.724	0.403
8	1.015	1.375	0.685	-0.331	0.695
9	0.879	1.416	0.612	-0.267	0.753
High	0.524	1.351	0.086	-0.437	0.689
Low - High	0.152	0.393	1.183	1.031	0.166
p-value	0.772	0.424	0.025		

TABLE 14 (Continued)

Panel E: Sort on long-run value to book ($v(\theta_{it}; \alpha_j) - b_{it}$)

	Arbitrage Capital				
	Low (84 months)	Medium (96 months)	High (84 months)	High-Low	*p*-value
$v(\theta_{it}; \alpha_j) - b_{it}$					
Low	0.688	1.299	0.857	0.169	0.864
2	0.902	1.455	0.960	0.058	0.944
3	0.564	1.277	0.874	0.310	0.711
4	0.790	1.392	0.907	0.117	0.899
5	1.019	1.313	0.934	-0.084	0.926
6	0.908	1.223	0.911	0.003	0.997
7	1.066	1.411	0.726	-0.340	0.698
8	0.929	1.604	0.622	-0.307	0.744
9	0.987	1.667	0.550	-0.436	0.670
High	1.036	1.494	0.600	-0.436	0.697
Low - High	-0.348	-0.195	0.258	0.606	0.410
p-value	0.503	0.688	0.620		

This table presents average monthly returns of portfolios sorted on log market-to-book (or its components) conditional on arbitrage capital availability at portfolio formation following Jylha and Suominen (2011) and Kokkonen and Suominen (2015). The time period is from Jul 1990 – Jun 2011. Each of the 22 portfolio formations for which data is available is classified into low, medium, or high arbitrage capital availability environment based on hedge funds assets under management in June of that year scaled by the average CRSP market capitalization over the previous 12 months. All monthly return observations until the next portfolio rebalancing are allocated to that category, resulting in three (approximately) equal-sized periods: low (84 months), medium (96 months), and high (84 months). Portfolio returns are prior period gross return weighted (RW). The time period is Jul 1990 – Jun 2012. Portfolios are formed every June 30 using NYSE breakpoints and rebalanced annually.

Appendix A. Definitions of variables

M/B COMPONENTS	
$m_{it} - b_{it}$	Natural logarithm of the market-to-book ratio for firm *i* at time *t*.
$m_{it} - v(\theta_{it};\ \alpha_j)$	Total error, i.e. the component of $m_{it} - b_{it}$ resulting from stock price deviations from valuations implied by long-run sector-specific multiples.
$m_{it} - v(\theta_{it};\ \alpha_{jt})$	Firm-specific error, i.e. the component of $m_{it} - b_{it}$ resulting from stock price deviations from valuations implied by sector valuation multiples calculated at time *t*.
$v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$	Sector error, i.e. the component of $m_{it} - b_{it}$ resulting from valuations implied by current sector multiples deviating from valuations implied by long-run multiples.
$v(\theta_{it};\ \alpha_j) - b_{it}$	Long-run value-to-book, i.e. the component of $m_{it} - b_{it}$ due to differences between valuations implied by long-run multiples and current book values.
INPUTS TO VALUATION	
m	Natural logarithm of market value of equity obtained on June 30 from CRSP.
b	Natural logarithm of book value of common equity (CEQ) plus balance sheet deferred taxes (TXDB) at fiscal year-end from Compustat. Observations with negative book values are excluded.
ni^{+}	Natural logarithm of the absolute value of net income (NI) at fiscal year end from Compustat.
$I_{<0}$	Indicator variable equal to one if net income (NI) is negative and zero otherwise.
LEV	Book leverage, defined as long-term debt (DLTT) plus debt in short-term liabilities (DLC) divided by total assets (AT) at fiscal year end from Compustat
Growth (robustness checks)	Past growth in sales (SALE) over the years t to t-3.
CONTROLS	
m	Natural logarithm of market value of equity obtained on June 30 from CRSP.
β^{-}_{post}	Downside beta, estimated by regressing firm-level daily stock returns on the value-weighted CRSP market index, conditional on market returns being lower than the sample average. The estimation is done over a window of 12 months starting July t until June t+1. A minimum of 60 daily return observations is required.
β^{+}_{post}	Upside beta, estimated by regressing firm-level daily stock returns on the value-weighted CRSP market index, conditional on market returns being higher than the sample average. The estimation is done over a window of 12 months starting July t until June t+1. A minimum of 60 daily return observations is required.
$IVol_{post}$	Idiosyncratic volatility of a stock, i.e. the portion of total stock return volatility unexplained by the market. IVol is calculated as the standard deviation of the residuals obtained from the regression used to calculate the unconditional market beta over a window of 12 months starting July t until June t+1.
β_{pre}	Market beta, estimated by regressing firm-level daily stock returns on the value-weighted CRSP market index. The estimation is done over a window of 12 months starting July t-1 until June t. A minimum of 60 daily return observations is required.

$IVol_{pre}$	The idiosyncratic volatility of a stock, i.e. the portion of total stock return volatility unexplained by the market. IVol is calculated as the standard deviation of the residuals obtained from the regression used to calculate the unconditional market beta over a window of 12 months starting July t-1 until June t.
Illiquidity	The daily ratio of absolute stock return to its dollar volume, averaged over a window of 12 months starting July t-1 until June t (Amihud (2002)).
OP	Operating profitability defined as gross profitability (REVT – COGS – XSGA - XINT) divided by book equity (CEQ) as of fiscal year end from Compustat (Fama and French (2015)).
Inv	Investment, defined as the percentage change in total assets (AT) from Compustat (Fama and French (2015)).
Ret^{-2-12}	Prior buy-and-hold 11-month stock return with a lag of 2 months (-2; -12).
Ret^{-1}	Prior one month stock return.
OLEV	Operating leverage, defined as cost of goods sold (COGS), plus selling, general and administrative expenses (XSGA) divided by total assets (AT) as of fiscal year end from Compustat (Novy-Marx (2011)).
LEV	Book leverage, defined as long-term debt (DLTT) plus debt in short-term liabilities (DLC) divided by total assets (AT) at fiscal year end from Compustat.
Duration	Equity duration following Dechow, Sloan, and Soliman (2004).
RISK PROXIES	
RRating	A discrete variable taking the values 1, 2, 3, 4 for low risk, medium risk, high risk, and speculative risk, respectively. These risk ratings are assigned by equity research analysts of a major financial institution.
LIMITS TO ARMITRAGE PROXIES	
RI	Residual institutional ownership 2 quarters prior to portfolio formation, computed as the residual from the following regression model estimated quarterly: $\log(INST_{it}/(1-INST_{it})) = \alpha + \beta LogSZ_{it} + \gamma(LogSZ_{it})^2$, where INST is institutional ownership and LogSZ is the logarithm of market value of equity. Values of INST below 0.0001 and above 0.9999 are replaced with 0.0001 and 0.9999 respectively (Nagel (2005)). Data from Thomson 13f Holdings.
$IVol_{pre}$	The idiosyncratic volatility of a stock, i.e. the portion of total stock return volatility unexplained by the market. IVol is calculated as the standard deviation of the residuals obtained from the regression used to calculate the unconditional market beta over a window of 12 months starting July t-1 until June t.
HF AUM	Hedge funds assets under management scaled by the average CRSP market capitalization of the previous 12 months. Data from Jylha and Suominen (2011) and Kokkonen and Suominen (2015).

Internet Appendix. Additional results and robustness tests

TABLE A1

Sorts on market-to-book and its components within size quintiles (RW)

Panel A: Market-to-book ($m_{it} - b_{it}$) sort conditional on size

	Size						
	Small	2	3	4	Big	Small-Big	*p*-value
$\underline{m_{it} - b_{it}}$							
Low	1.536	1.421	1.498	1.357	1.169	0.368	0.167
2	1.552	1.448	1.261	1.210	1.102	0.450	0.041
3	1.461	1.351	1.278	1.215	1.042	0.419	0.022
4	1.331	1.399	1.318	1.160	1.016	0.315	0.094
High	1.043	1.077	1.103	1.132	0.947	0.095	0.663
Low – High	0.493	0.344	0.395	0.225	0.221	0.272	0.198
p-value	0.013	0.081	0.049	0.257	0.262		

Panel B: Total error ($m_{it} - v(\theta_{it}; \alpha_j)$) sort conditional on size

	Size						
	Low	2	3	4	High	Small-Big	*p*-value
$\underline{m_{it} - v(\theta_{it}; \alpha_j)}$							
Low	1.568	1.414	1.420	1.449	1.181	0.386	0.141
2	1.474	1.451	1.452	1.294	1.089	0.385	0.068
3	1.398	1.464	1.263	1.183	1.097	0.301	0.126
4	1.305	1.285	1.250	1.131	0.919	0.386	0.043
High	0.882	1.007	1.060	1.054	0.990	-0.108	0.591
Low – High	0.685	0.407	0.359	0.395	0.191	0.495	0.010
p-value	0.000	0.017	0.050	0.022	0.260		

Panel C: Firm-specific error ($m_{it} - v(\theta_{it}; \alpha_{jt})$) sort conditional on size

	Size						
	Low	2	3	4	High	Small-Big	*p*-value
$\underline{m_{it} - v(\theta_{it}; \alpha_{jt})}$							
Low	1.594	1.408	1.366	1.394	1.200	0.394	0.114
2	1.553	1.464	1.440	1.315	1.020	0.533	0.015
3	1.362	1.359	1.253	1.105	1.036	0.326	0.100
4	1.322	1.310	1.278	1.170	0.989	0.332	0.075
High	0.881	1.043	1.055	1.092	1.004	-0.123	0.544
Low – High	0.712	0.365	0.311	0.302	0.195	0.517	0.004
p-value	0.000	0.014	0.068	0.046	0.176		

TABLE A1 (Continued)

Panel D: Sector error ($v(\theta_{it};\alpha_{jt})_t - v(\theta_{it};\alpha_j)$) sort conditional on size

	Size						
	Low	2	3	4	High	Small-Big	*p*-value
$\underline{v(\theta_{it};\alpha_{jt}) - v(\theta_{it};\alpha_j)}$							
Low	1.124	1.363	1.367	1.325	1.144	-0.020	0.931
2	1.391	1.374	1.289	1.202	1.102	0.288	0.182
3	1.329	1.241	1.245	1.244	0.995	0.334	0.118
4	1.358	1.341	1.312	1.268	1.135	0.222	0.281
High	1.276	1.115	1.159	1.042	0.910	0.367	0.094
Low - High	-0.153	0.248	0.208	0.284	0.234	-0.386	0.041
p-value	0.344	0.153	0.265	0.128	0.237		

Panel E: Long-run value to book ($v(\theta_{it};\alpha_j) - b_{it}$) sort conditional on size

	Size						
	Low	2	3	4	High	Small-Big	*p*-value
$\underline{v(\theta_{it};\alpha_j) - b_{it}}$							
Low	1.221	1.222	1.255	1.143	1.134	0.086	0.691
2	1.312	1.287	1.295	1.148	0.990	0.322	0.100
3	1.268	1.389	1.261	1.207	1.076	0.192	0.285
4	1.341	1.383	1.238	1.238	0.943	0.398	0.030
High	1.222	1.152	1.228	1.229	1.080	0.142	0.553
Low – High	-0.001	0.069	0.027	-0.086	0.054	-0.056	0.761
p-value	0.993	0.676	0.867	0.614	0.728		

This table presents average monthly returns of prior period gross return weighted (RW) portfolios sorted on log market-to-book (or its components) conditional on size. Stocks are first sorted into NYSE-based size quintiles, and then sorted on log market-to-book or its components within each size quintile. See Appendix A for detailed definitions. The time period is Jul 1975 – Jun 2013. Portfolios are formed every June 30 using NYSE breakpoints and rebalanced annually.

TABLE A2

Sorts on market-to-book and its components within size quintiles (VW)

Panel A: Market-to-book ($m_{it} - b_{it}$) sort conditional on size

	Size						
	Low	2	3	4	High	Small-Big	*p*-value
$\underline{m_{it} - b_{it}}$							
Low	1.552	1.359	1.463	1.292	1.019	0.533	0.040
2	1.559	1.405	1.226	1.166	1.015	0.543	0.013
3	1.483	1.330	1.231	1.170	0.967	0.517	0.013
4	1.410	1.391	1.316	1.130	1.014	0.396	0.056
High	1.206	1.160	1.123	1.158	0.866	0.340	0.159
Low – High	0.346	0.199	0.340	0.134	0.153	0.193	0.368
p-value	0.122	0.314	0.096	0.527	0.402		

Panel B: Total error ($m_{it} - v(\theta_{it}; \alpha_j)$) sort conditional on size

	Size						
	Low	2	3	4	High	Small-Big	*p*-value
$\underline{m_{it} - v(\theta_{it}; \alpha_j)}$							
Low	1.594	1.368	1.424	1.386	1.084	0.509	0.045
2	1.566	1.466	1.418	1.257	0.953	0.613	0.008
3	1.509	1.415	1.213	1.107	1.101	0.408	0.059
4	1.451	1.309	1.239	1.123	0.855	0.596	0.008
High	1.048	1.077	1.070	1.089	0.861	0.187	0.407
Low – High	0.546	0.291	0.354	0.297	0.224	0.322	0.070
p-value	0.001	0.094	0.064	0.109	0.174		

Panel C: Firm-specific error ($m_{it} - v(\theta_{it}; \alpha_{jt})$) sort conditional on size

	Size						
	Low	2	3	4	High	Small-Big	*p*-value
$\underline{m_{it} - v(\theta_{it}; \alpha_{jt})}$							
Low	1.623	1.367	1.368	1.308	1.095	0.528	0.026
2	1.596	1.497	1.377	1.298	1.002	0.593	0.008
3	1.508	1.341	1.245	1.058	0.929	0.578	0.014
4	1.408	1.318	1.265	1.135	0.961	0.447	0.040
High	1.074	1.094	1.063	1.129	0.879	0.194	0.389
Low - High	0.549	0.272	0.305	0.179	0.216	0.334	0.051
p-value	0.000	0.079	0.091	0.273	0.129		

Panel D: Sector error ($v(\theta_{it}; \alpha_{jt})_t - v(\theta_{it}; \alpha_j)$) sort conditional on size

	Size						
	Low	2	3	4	High	Small-Big	*p*-value
$\underline{v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)}$							
Low	1.236	1.297	1.344	1.274	1.033	0.202	0.396
2	1.459	1.371	1.316	1.178	0.952	0.507	0.031
3	1.390	1.288	1.226	1.269	0.837	0.553	0.014
4	1.365	1.359	1.291	1.249	1.087	0.278	0.230
High	1.370	1.175	1.125	0.989	0.894	0.476	0.047
Low – High	-0.135	0.122	0.219	0.285	0.140	-0.274	0.144
p-value	0.425	0.475	0.214	0.119	0.427		

TABLE A2 (Continued)

Panel E: Long-run value to book ($v(\theta_{it};\ \alpha_j) - b_{it}$) sort conditional on size

	Size						
	Low	2	3	4	High	Small-Big	*p*-value
$v(\theta_{it};\ \alpha_j) - b_{it}$							
Low	1.232	1.191	1.191	1.097	1.018	0.214	0.344
2	1.217	1.290	1.311	1.117	0.896	0.320	0.106
3	1.350	1.362	1.199	1.144	0.977	0.374	0.056
4	1.417	1.412	1.293	1.271	0.892	0.525	0.007
High	1.339	1.206	1.229	1.223	1.000	0.339	0.190
Low - High (Raw)	-0.108	-0.015	-0.038	-0.125	0.017	-0.125	0.574
p-value	0.578	0.924	0.816	0.502	0.915		

This table presents average monthly returns of value-weighted (VW) portfolios sorted on log market-to-book (or its components) conditional on size. Stocks are first sorted into NYSE-based size quintiles, and then sorted on log market-to-book or its components within each size quintile. See Appendix A for detailed definitions. The time period is Jul 1975 – Jun 2013. Portfolios are formed every June 30 using NYSE breakpoints and rebalanced annually.

TABLE A3

Fama-MacBeth regressions of firm-level returns on log market-to-book and its components (VW)

	1	2	3	4	5	6
Intercept	1.114	1.093	1.114	3.297	3.269	3.352
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$m_{it} - b_{it}$	-0.129			-0.146		
	(0.138)			(0.102)		
First decomposition						
$m_{it} - v(\theta_{it}; \alpha_j)$		-0.220			-0.163	
		(0.024)			(0.069)	
$v(\theta_{it}; \alpha_j) - b_{it}$		-0.002			-0.094	
		(0.986)			(0.423)	
Comprehensive decomposition						
$m_{it} - v(\theta_{it}; \alpha_{jt})$			-0.212			-0.160
			(0.020)			(0.073)
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$			-0.261			-0.173
			(0.437)			(0.546)
$v(\theta_{it}; \alpha_j) - b_{it}$			0.053			-0.112
			(0.626)			(0.342)
Controls						
m				-0.211	-0.208	-0.207
				(0.000	(0.000)	(0.000)
β^{+}_{post}				0.185	0.175	0.168
				(0.222	(0.246)	(0.258)
β^{-}_{post}				0.513	0.496	0.495
				(0.005	0.008)	(0.007)
$IVol_{post}$				-63.692	-63.187	-63.062
				(0.000	(0.000)	(0.000)
Illiquidity				0.019	0.017	0.017
				(0.001	(0.003)	(0.002)
$Ret^{-2\text{-}12}$				0.398	0.416	0.408
				(0.020	(0.012)	(0.012)
Ret^{-1}				-0.039	-0.039	-0.040
				(0.000	(0.000)	(0.000)
OP				0.591	0.526	0.532
				(0.006	(0.016)	(0.013)
Inv				-0.248	-0.226	-0.219
				(0.028	(0.047)	(0.054)
Adj. R^2	0.026	0.035	0.052	0.178	0.185	0.193
N	456	456	456	456	456	456

This table reports estimation results of Fama-MacBeth regressions of monthly firm-level stock returns on log market-to-book, its components, and control variables over the period Jul 1975 – Jun 2013. Regressions are value weighted (VW). Reported R^2s are cross-sectional means of monthly adjusted R^2s. See Appendix A for detailed definitions of all variables.

TABLE A4

Cash flow risk – Campbell and Vuoltenaaho (2004) (VW)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it};\ \alpha_j)$	$m_{it} - v(\theta_{it};\ \alpha_{jt})$	$v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$	$v(\theta_{it};\ \alpha_j) - b_{it}$
Low	0.253	0.284	0.262	0.154	0.177
2	0.186	0.202	0.211	0.150	0.152
3	0.188	0.217	0.206	0.135	0.156
4	0.201	0.172	0.204	0.189	0.184
5	0.189	0.189	0.166	0.180	0.194
6	0.201	0.189	0.158	0.214	0.219
7	0.188	0.161	0.166	0.181	0.201
8	0.196	0.169	0.157	0.184	0.182
9	0.165	0.144	0.152	0.162	0.164
High	0.108	0.130	0.119	0.154	0.112
Low - High	0.144	0.154	0.143	0.000	0.065
t-stat	3.573	3.688	4.312	-0.006	2.462
p-value	0.000	0.000	0.000	1.000	0.014

This table reports the sensitivity (beta) of monthly portfolio returns to market-level cash flow shocks as in Campbell and Vuoltenaaho (2004). Cash flow shocks are obtained from a VAR-based decomposition of the market return estimated over the period Jan 1929 – Jun 2013. Portfolio returns are value weighted (VW). Sample period is Jul 1975–Jun 2013. Portfolios are formed every June 30 using NYSE breakpoints and rebalanced annually. See Appendix A for detailed definitions. *t*-statistics and the associated *p*-values are based on Newey-West standard errors (lag of 5).

TABLE A5

Long-run consumption risk (VW)

Panel A: Ultimate consumption risk in returns (Parker and Julliard (2005)) (N=152 quarters)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it};\ \alpha_j)$	$m_{it} - v(\theta_{it};\ \alpha_{jt})$	$v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$	$v(\theta_{it};\ \alpha_j) - b_{it}$
Low	0.543	0.350	0.364	0.267	0.133
2	0.243	0.418	0.267	0.155	0.006
3	0.208	0.338	0.260	0.160	0.119
4	0.146	0.206	0.243	0.083	0.193
5	0.130	0.290	0.255	0.076	0.314
6	0.161	0.152	0.210	0.066	0.289
7	0.222	0.189	0.162	0.132	0.233
8	0.161	0.146	0.133	0.066	0.186
9	0.190	0.043	0.147	0.106	0.089
High	0.076	0.078	0.047	0.015	0.040
Low - High	0.463	0.264	0.307	0.254	0.098
t-stat	2.095	1.445	1.595	1.458	0.592
p-value	0.038	0.150	0.113	0.147	0.555

Panel B: Consumption risk in cash flows (dividends) (Bansal, Dittmar and Lundblad (2005)) (N=148 quarters)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it};\ \alpha_j)$	$m_{it} - v(\theta_{it};\ \alpha_{jt})$	$v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$	$v(\theta_{it};\ \alpha_j) - b_{it}$
Low	4.575	1.548	1.592	2.188	2.241
2	-1.859	1.533	5.609	-3.765	4.052
3	2.499	-1.684	-2.046	-1.138	-1.397
4	2.656	-0.637	0.378	-0.007	-3.230
5	2.402	3.738	1.154	-1.847	-2.033
6	1.965	0.997	-2.421	3.479	1.786
7	-0.799	-0.452	-0.105	1.179	-1.721
8	1.641	1.028	0.008	3.930	1.121
9	0.617	0.688	-0.717	5.191	2.743
High	-1.029	-4.435	-0.626	-3.008	-0.708
Low - High	5.604	5.983	2.218	5.197	2.949
t-stat	0.463	0.840	0.535	0.544	0.444
p-value	0.644	0.402	0.594	0.587	0.658

Panel C: Ultimate consumption risk in cash flows (dividends) (N=148 quarters)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it};\ \alpha_j)$	$m_{it} - v(\theta_{it};\ \alpha_{jt})$	$v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$	$v(\theta_{it};\ \alpha_j) - b_{it}$
Low	0.158	-0.461	-0.017	-0.432	-0.332
2	-0.257	-0.177	-0.226	0.107	-0.438
3	-0.415	0.102	-0.265	0.086	-0.165
4	-0.277	0.112	-0.329	0.375	0.294
5	-0.418	-0.332	-0.102	-0.037	0.150
6	-0.416	-0.210	-0.083	-0.342	-0.096
7	0.195	-0.243	-0.281	-0.189	-0.002
8	-0.015	-0.329	0.324	-0.015	-0.058
9	-0.208	-0.042	0.009	-0.620	-0.108
High	0.306	-0.012	-0.099	0.353	-0.192
Low - High	-0.148	-0.449	0.083	-0.785	-0.140
t-stat	-0.367	-0.886	0.212	-1.214	-0.361
p-value	0.714	0.377	0.832	0.227	0.718

This table presents exposures of returns and cash flows of portfolios sorted on log market-to-book and its components to long-run consumption. Panel A reports the sensitivity (beta) of quarterly portfolio returns to ultimate consumption growth as in Parker and Julliard (2005). Ultimate consumption growth is the log growth rate of real per capita consumption of non-durable goods from quarter t to quarter t+11. Quarterly portfolio returns are obtained by cumulating monthly returns and are converted to real using the PCE deflator. Portfolio returns are value-weighted (VW). Sample period is 1975:Q3 – 2013:Q2. Panel B reports the sensitivity (beta) of portfolio-level dividends to long-run past consumption growth as in Bansal, Dittmar and Lundblad (2005). Quarterly portfolio dividends are extracted from CRSP data using monthly returns with and without dividends (value-weighted (VW)) and aggregated to quarterly. The resulting series is converted to real using the PCE deflator, seasonally-adjusted by taking a 4-quarter moving average, and log growth rates are taken. Long-run past consumption growth is an 8-quarter moving average of log quarterly growth rates in real per capita consumption of non-durables and services over t-1 to t-8. Sample period is 1976:Q3 – 2013:Q2. Panel C reports the sensitivity (beta) of portfolio-level dividends from Panel B to ultimate consumption growth from Panel A. Portfolios are formed every June 30 using NYSE breakpoints and rebalanced annually. See Appendix A for detailed definitions. t-statistics and the associated p-values are based on Newey-West standard errors (lag of 5).

TABLE A6

Exposure to investment-specific technology shocks (Kogan and Papanikolau (2014)) (N=456 months)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it}; \alpha_j)$	$m_{it} - v(\theta_{it}; \alpha_{jt})$	$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$	$v(\theta_{it}; \alpha_j) - b_{it}$
Low	0.417	0.584	0.622	0.527	0.382
2	0.276	0.515	0.403	0.522	0.297
3	0.258	0.397	0.413	0.462	0.426
4	0.326	0.408	0.354	0.331	0.486
5	0.344	0.255	0.375	0.386	0.482
6	0.343	0.321	0.400	0.490	0.450
7	0.409	0.353	0.335	0.458	0.390
8	0.347	0.300	0.328	0.391	0.391
9	0.407	0.345	0.292	0.379	0.333
High	0.476	0.545	0.586	0.500	0.515
Low - High	-0.059	0.039	0.036	0.027	-0.133
t-stat	-0.743	0.442	0.668	0.213	-2.230
p-value	0.458	0.659	0.505	0.832	0.026

This table presents the sensitivity (beta) of portfolio returns to investment-specific technology shocks of Kogan and Papanikolau (2014). The sensitivities are estimated as portfolio return betas with respect to a factor mimicking portfolio long investment goods producers and short consumer goods producers (IMC factor). Portfolio returns and the IMC factor return are value-weighted (VW). Portfolios are formed every June 30 using NYSE breakpoints and rebalanced annually. Betas are not estimated for investment goods producers and service firms, and the portfolios are sorted after these firms are excluded. Industry classifications are from Gomes, Kogan, and Yogo (2009). Sample period is Jul 1975 – Jun 2013. See Appendix A for detailed definitions. *t*-statistics and the associated *p*-values are based on Newey-West standard errors (lag of 5).

TABLE A7
Additional results on operating leverage

Panel A: Sensitivity to an operating leverage factor (RW portfolios)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it}; \alpha_j)$	$m_{it} - v(\theta_{it}; \alpha_{jt})$	$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$	$v(\theta_{it}; \alpha_j) - b_{it}$
Low	-0.296	-0.266	-0.292	-0.371	-0.216
2	-0.207	-0.225	-0.201	-0.216	-0.225
3	-0.173	-0.156	-0.180	-0.154	-0.224
4	-0.141	-0.157	-0.151	-0.061	-0.220
5	-0.136	-0.105	-0.145	-0.057	-0.167
6	-0.146	-0.157	-0.175	-0.091	-0.126
7	-0.175	-0.135	-0.167	-0.064	-0.120
8	-0.146	-0.139	-0.155	-0.097	-0.123
9	-0.208	-0.197	-0.221	-0.136	-0.221
High	-0.290	-0.309	-0.285	-0.368	-0.330
Low - High	-0.006	0.043	-0.007	-0.003	0.114
t-stat	-0.042	0.354	-0.074	-0.023	1.031
p-value	0.967	0.723	0.941	0.982	0.303

Panel B: Sensitivity to an operating leverage factor (VW portfolios)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it}; \alpha_j)$	$m_{it} - v(\theta_{it}; \alpha_{jt})$	$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$	$v(\theta_{it}; \alpha_j) - b_{it}$
Low	-0.271	-0.218	-0.216	-0.382	-0.288
2	-0.257	-0.185	-0.220	-0.246	-0.353
3	-0.198	-0.162	-0.131	-0.079	-0.433
4	-0.234	-0.204	-0.226	-0.018	-0.352
5	-0.270	-0.155	-0.181	-0.154	-0.211
6	-0.174	-0.219	-0.349	-0.160	-0.084
7	-0.191	-0.254	-0.174	-0.045	-0.031
8	-0.127	-0.143	-0.186	-0.147	0.003
9	-0.130	-0.191	-0.152	-0.094	0.003
High	-0.158	-0.214	-0.250	-0.332	-0.229
Low - High	-0.113	-0.005	0.033	-0.049	-0.059
t-stat	-0.838	-0.033	0.382	-0.386	-0.521
p-value	0.402	0.973	0.703	0.699	0.603

Panel C: Firm-level regressions including *OLEV*

	1	2	3
Intercept	2.971	2.715	2.687
	(0.000)	(0.000)	(0.000)
$m_{it} - b_{it}$	-0.264		
	(0.000)		
First decomposition			
$m_{it} - v(\theta_{it}; \alpha_j)$		-0.383	
		(0.000)	
$v(\theta_{it}; \alpha_j) - b_{it}$		-0.052	
		(0.501)	
Comprehensive decomposition			
$m_{it} - v(\theta_{it}; \alpha_{jt})$			-0.389
			(0.000)
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$			-0.415
			(0.107)
$v(\theta_{it}; \alpha_j) - b_{it}$			-0.032
			(0.685)
OLEV	0.069	0.073	0.064
	(0.080)	(0.064)	(0.084)
Controls: m, β^{+}_{post}, β^{-}_{post}, $IVol_{post}$, *Illiquidity*, Ret_{-2-12}, Ret_{-1}, *OP*, *Inv*			
Adj R2	0.080	0.081	0.082
N	456	456	456

This table presents additional results on operating leverage. Panels A and B report the sensitivity (beta) of portfolio returns to an operating leverage factor based on the *OLEV* measure of Novy-Marx (2011). Operating leverage factor is a monthly return of a long short/strategy that is long in the top quintile of *OLEV* and short in the bottom quintile of *OLEV* using on NYSE breakpopints. Portfolio returns are prior gross return weighted (RW) in Panel A and value weighted (VW) in Panel B. Operating leverage factor return is always value-weighted (VW). Portfolios are formed every June 30 using NYSE breakpoints and rebalanced annually. Sample period is Jul 1975 – Jun 2013. *t*-statistics and the associated *p*-values are based on Newey-West standard errors (lag of 5). Panel C reports results of Fama-MacBeth regressions of monthly firm-level returns on market-to-book and its components controlling additionally for operating leverage (*OLEV*). Following Asparouhova, Bessembinder, and Kalcheva (2010), regressions are weighted by prior period gross returns (RW). Reported R^2s are cross-sectional means of monthly adjusted R^2s. See Appendix A for detailed definitions.

TABLE A8
Additional results on duration

	1	2	3
Intercept	2.685	2.381	2.347
	(0.000)	(0.000)	(0.000)
$m_{it} - b_{it}$	-0.304		
	(0.000)		
First decomposition			
$m_{it} - v(\theta_{it};\ \alpha_j)$		-0.432	
		(0.000)	
$v(\theta_{it};\ \alpha_j) - b_{it}$		-0.092	
		(0.237)	
Comprehensive decomposition			
$m_{it} - v(\theta_{it};\ \alpha_{jt})$			-0.444
			(0.000)
$v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$			-0.364
			(0.179)
$v(\theta_{it};\ \alpha_j) - b_{it}$			-0.056
			(0.486)
Duration	0.028	0.031	0.029
	(0.003)	(0.001)	(0.002)
Controls: m, β^{+}_{post}, β^{-}_{post}, $IVol_{post}$, *Illiquidity*, $Ret_{-2\text{-}12}$, Ret_{-1}, *OP*, *Inv*			
Adj R2	0.079	0.080	0.082
N	456	456	456

Panel B: Chen (2017) buy-and-hold portfolio dividend growth rates (geometric average of years 1-10) (VW)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it};\ \alpha_j)$	$m_{it} - v(\theta_{it};\ \alpha_{jt})$	$v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$	$v(\theta_{it};\ \alpha_j) - b_{it}$
Low	4.195	4.284	4.168	2.912	2.503
2	1.346	2.537	2.497	3.370	1.308
3	1.883	2.573	3.116	3.328	2.370
4	1.482	2.766	3.258	2.804	3.053
5	2.870	2.982	2.575	3.459	2.977
6	2.470	2.360	2.633	4.074	5.061
7	3.319	3.100	3.810	4.623	3.794
8	4.631	3.795	4.428	3.551	5.100
9	5.773	5.598	4.651	3.838	6.726
High	6.656	4.875	4.942	4.387	6.554
Low - High	-2.461	-0.591	-0.775	-1.476	-4.052
t-stat	-1.343	-0.347	-0.532	-1.578	-5.050
p-value	0.190	0.731	0.599	0.126	0.000

This table presents additional results on duration. Panel A reports results of Fama-MacBeth regressions of future monthly firm-level returns on market-to-book and its components controlling additionally for duration of Dechow, Sloan, and Soliman (2004). Following Asparouhova, Bessembinder, and Kalcheva (2010), regressions are weighted by prior period gross returns (RW). Reported R^2s are cross-sectional means of monthly adjusted R^2s. Panel B reports buy-and-hold portfolio dividend growth rates following Chen (2017). For each of the ten years following portfolio formation, annual dividends are extracted from monthly CRSP data using returns with and without dividends (added up from July to June). Portfolio returns are value-weighted (VW). Geometric average growth rates in dividends from year 1 to year 10 is then computed and time-series averages across 33 portfolio formations (1975-2007) are taken. Portfolios are formed every June 30 using NYSE breakpoints and rebalanced annually. See Appendix A for detailed definitions. *t*-statistics and *p*-values are based on Newey-West adjusted standard errors (lag of 5).

TABLE A9

Limits to arbitrage: short-sale constraints proxied by institutional ownership (VW)

Panel A: Double sort with log market-to-book ($m_{it} - b_{it}$) conditional on size

Within Small	Residual Institutional Ownership						
$m_{it} - b_{it}$	Low	2	3	4	High	High-Low	*p*-value
Low - High	0.646	0.409	0.092	0.090	0.389	-0.257	0.334
p-value	0.015	0.144	0.730	0.723	0.122		

Within Big	Residual Institutional Ownership						
$m_{it} - b_{it}$	Low	2	3	4	High	High-Low	*p*-value
Low - High	0.062	0.210	0.142	0.298	0.095	0.033	0.926
p-value	0.853	0.379	0.522	0.179	0.733		

Panel B: Double sort with total error ($m_{it} - v(\theta_{it}; \alpha_j)$) conditional on size

Within Small	Residual Institutional Ownership						
$m_{it} - v(\theta_{it}; \alpha_j)$	Low	2	3	4	High	High-Low	*p*-value
Low - High	0.802	0.377	0.159	0.302	0.388	-0.414	0.093
p-value	0.000	0.111	0.448	0.158	0.061		

Within Big	Residual Institutional Ownership						
$m_{it} - v(\theta_{it}; \alpha_j)$	Low	2	3	4	High	High-Low	*p*-value
Low - High	0.154	0.172	0.248	0.222	0.370	0.216	0.461
p-value	0.571	0.448	0.228	0.334	0.138		

Panel C: Double sort with firm-specific error ($m_{it} - v(\theta_{it}; \alpha_{jt})$) conditional on size

Within Small	Residual Institutional Ownership						
$m_{it} - v(\theta_{it}; \alpha_{jt})$	Low	2	3	4	High	High-Low	*p*-value
Low - High	0.814	0.396	0.105	0.186	0.308	-0.506	0.033
p-value	0.000	0.066	0.596	0.364	0.120		

Within Big	Residual Institutional Ownership						
$m_{it} - v(\theta_{it}; \alpha_{jt})$	Low	2	3	4	High	High-Low	*p*-value
Low - High	-0.036	0.172	0.238	0.272	0.022	0.059	0.844
p-value	0.891	0.419	0.207	0.177	0.924		

Panel D: Double sort with sector error ($v(\theta_{it}; \alpha_{jt})_t - v(\theta_{it}; \alpha_j)$) conditional on size

Within Small	Residual Institutional Ownership						
$v(\theta_{it}; \alpha_{jt})_t - v(\theta_{it}; \alpha_j)$	Low	2	3	4	High	High-Low	*p*-value
Low - High	0.164	0.021	0.218	0.140	0.171	0.007	0.976
p-value	0.452	0.926	0.308	0.547	0.421		

Within Big	Residual Institutional Ownership						
$v(\theta_{it}; \alpha_{jt})_t - v(\theta_{it}; \alpha_j)$	Low	2	3	4	High	High-Low	*p*-value
Low - High	0.556	0.347	0.312	0.178	0.366	-0.190	0.545
p-value	0.044	0.132	0.149	0.471	0.142		

TABLE A9 (Continued)

Panel E: Double sort with long-run value-to-book ($v(\theta_{it}; \alpha_j) - b_{it}$) conditional on size

Within Small	Residual Institutional Ownership						
$v(\theta_{it}; \alpha_j) - b_{it}$	Low	2	3	4	High	High-Low	*p*-value
Low - High	0.211	0.098	-0.124	-0.360	0.071	-0.140	0.576
p-value	0.377	0.628	0.576	0.131	0.745		

Within Big	Residual Institutional Ownership						
$v(\theta_{it}; \alpha_j) - b_{it}$	Low	2	3	4	High	High-Low	*p*-value
Low - High	-0.086	0.011	-0.124	-0.069	-0.299	-0.213	0.512
p-value	0.777	0.961	0.558	0.765	0.245		

This table presents average returns of long/short strategies based on log market-to-book (or its components) across institutional ownership quintiles conditional on size, following Nagel (2003). Stocks are first sorted into small and big based on 50^{th} percentile of market capitalization of NYSE firms. Within those two categories separately, stocks are then sorted independently into quintiles based on log market-to-book (or its components) and residual institutional ownership. Residual institutional ownership is as of two quarters prior to portfolio formation date (end of December). Residual institutional ownership is orthogonalized with respect to size and size-squared. See Appendix A for detailed definitions. Portfolio returns are value-weighted (VW). The time period is Jul 1975 – Jun 2013. Portfolios are formed every June 30 using NYSE breakpoints and rebalanced annually.

TABLE A10

Limits to arbitrage: noise trader risk proxied by idiosyncratic volatility (VW)

Panel A: Double sort with log market-to-book ($m_{it} - b_{it}$) conditional on size

Within Small	Idiosyncratic Volatility						
$m_{it} - b_{it}$	Low	2	3	4	High	High-Low	*p*-value
Low - High	0.121	-0.172	-0.024	0.238	0.578	0.457	0.113
p-value	0.557	0.336	0.906	0.278	0.022		

Within Big	Idiosyncratic Volatility						
$m_{it} - b_{it}$	Low	2	3	4	High	High-Low	*p*-value
Low - High	0.087	0.167	0.117	0.300	0.148	0.061	0.838
p-value	0.662	0.411	0.580	0.194	0.630		

Panel B: Double sort with total error ($m_{it} - v(\theta_{it}; \alpha_j)$) conditional on size

Within Small	Idiosyncratic Volatility						
$m_{it} - v(\theta_{it}; \alpha_j)$	Low	2	3	4	High	High-Low	*p*-value
Low - High	0.185	-0.016	0.274	0.217	0.584	0.399	0.092
p-value	0.263	0.916	0.104	0.223	0.004		

Within Big	Idiosyncratic Volatility						
$m_{it} - v(\theta_{it}; \alpha_j)$	Low	2	3	4	High	High-Low	*p*-value
Low - High	0.097	0.337	0.200	0.365	0.344	0.247	0.357
p-value	0.621	0.093	0.294	0.073	0.163		

Panel C: Double sort with firm-specific error ($m_{it} - v(\theta_{it}; \alpha_{jt})$) conditional on size

Within Small	Idiosyncratic Volatility						
$m_{it} - v(\theta_{it}; \alpha_{jt})$	Low	2	3	4	High	High-Low	*p*-value
Low - High	0.159	0.034	0.229	0.229	0.646	0.486	0.026
p-value	0.300	0.815	0.146	0.185	0.000		

Within Big	Idiosyncratic Volatility						
$m_{it} - v(\theta_{it}; \alpha_{jt})$	Low	2	3	4	High	High-Low	*p*-value
Low - High	0.145	0.109	0.261	0.266	0.247	0.102	0.691
p-value	0.442	0.563	0.179	0.134	0.263		

Panel D: Double sort with sector error ($v(\theta_{it}; \alpha_{jt})_t - v(\theta_{it}; \alpha_j)$) conditional on size

Within Small	Idiosyncratic Volatility						
$v(\theta_{it}; \alpha_{jt})_t - v(\theta_{it}; \alpha_j)$	Low	2	3	4	High	High-Low	*p*-value
Low - High	-0.119	0.005	-0.112	-0.097	0.076	0.194	0.420
p-value	0.461	0.976	0.533	0.623	0.715		

Within Big	Idiosyncratic Volatility						
$v(\theta_{it}; \alpha_{jt})_t - v(\theta_{it}; \alpha_j)$	Low	2	3	4	High	High-Low	*p*-value
Low - High	0.059	0.381	-0.036	0.113	0.253	0.194	0.512
p-value	0.766	0.072	0.870	0.622	0.298		

TABLE A10 (Continued)

Panel E: Double sort with long-run value-to-book ($v(\theta_{it}; \alpha_j) - b_{it}$) conditional on size

Within Small	Idiosyncratic Volatility						
$v(\theta_{it}; \alpha_j) - b_{it}$	Low	2	3	4	High	High-Low	*p*-value
Low - High	0.057	-0.343	-0.489	-0.084	0.345	0.287	0.217
p-value	0.696	0.039	0.007	0.626	0.082		
Within Big	Idiosyncratic Volatility						
$v(\theta_{it}; \alpha_j) - b_{it}$	Low	2	3	4	High	High-Low	*p*-value
Low - High	0.133	-0.087	-0.113	0.006	-0.140	-0.273	0.323
p-value	0.500	0.675	0.573	0.979	0.557		

This table presents average returns of long/short strategies based on log market-to-book (or its components) across idiosyncratic return volatility ($IVOL_{pre}$) quintiles conditional on size, following Ali, Hwang, and Trombley (2003). Stocks are first sorted into small and big based on 50th percentile of market capitalization of NYSE firms. Within those two categories separately, stocks are then sorted independently into quintiles based on log market-to-book (or its components) and idiosyncratic volatility. Idiosyncratic volatility is calculated as the standard deviation of residuals from a regression of daily stock returns on the CRSP value-weighted market return using 12 months prior to portfolio formation. See Appendix A for detailed definitions. Portfolio returns are value-weighted (VW). The time period is Jul 1975 – Jun 2013. Portfolios are formed every June 30 using NYSE breakpoints and rebalanced annually.

TABLE A11

Limits to arbitrage: time-series test using hedge funds assets under management (VW)

Panel A: Sort on market-to-book ($m_{it} - b_{it}$)

	Arbitrage Capital				
	Low (84 months)	Medium (96 months)	High (84 months)	High-Low	*p*-value
<u>$m_{it} - b_{it}$</u>					
Low	1.138	1.712	0.867	-0.271	0.756
2	0.420	1.262	0.874	0.455	0.529
3	0.662	1.397	0.911	0.248	0.726
4	0.092	1.162	0.698	0.607	0.369
5	0.503	1.535	0.928	0.425	0.533
6	0.670	1.441	0.574	-0.096	0.892
7	0.431	1.397	0.528	0.097	0.889
8	0.570	1.401	0.627	0.057	0.932
9	0.170	1.756	0.557	0.386	0.587
High	-0.027	1.623	0.717	0.744	0.324
Low – High	1.165	0.089	0.150	-1.016	0.163
p-value	0.024	0.853	0.771		

Panel B: Sort on total error ($m_{it} - v(\theta_{it}; \alpha_j)$)

	Arbitrage Capital				
	Low (84 months)	Medium (96 months)	High (84 months)	High-Low	*p*-value
<u>$m_{it} - v(\theta_{it}; \alpha_j)$</u>					
Low	0.820	1.725	1.048	0.228	0.815
2	0.691	1.612	0.531	-0.160	0.846
3	0.665	1.602	0.388	-0.277	0.722
4	0.208	1.210	1.033	0.825	0.267
5	0.788	1.482	0.586	-0.203	0.748
6	0.564	1.212	0.583	0.018	0.978
7	0.001	1.684	0.823	0.823	0.203
8	0.418	1.473	0.646	0.227	0.718
9	-0.016	1.467	0.618	0.634	0.343
High	0.072	1.552	0.754	0.681	0.395
Low - High (Raw)	0.748	0.173	0.294	-0.454	0.527
p-value	0.141	0.716	0.562		

TABLE A11 (Continued)

Panel C: Sort on firm-specific error ($m_{it} – v(\theta_{it}; \alpha_{jt})$)

	Arbitrage Capital				
	Low (84 months)	Medium (96 months)	High (84 months)	High-Low	*p*-value
$m_{it} – v(\theta_{it}; \alpha_{jt})$					
Low	0.828	1.520	0.608	-0.220	0.810
2	0.218	1.433	0.349	0.131	0.867
3	0.661	1.545	0.779	0.118	0.870
4	0.471	1.517	0.712	0.242	0.739
5	1.119	1.537	0.700	-0.419	0.555
6	0.074	1.497	0.721	0.647	0.355
7	0.118	1.373	0.564	0.446	0.484
8	-0.159	1.530	0.501	0.660	0.304
9	0.371	1.594	0.725	0.354	0.584
High	-0.127	1.611	0.845	0.972	0.255
Low - High	0.955	-0.091	-0.237	-1.192	0.044
p-value	0.828	1.520	0.608	-0.220	0.810

Panel D: Sort on sector error ($v(\theta_{it}; \alpha_{jt})_t – v(\theta_{it}; \alpha_j)$)

	Arbitrage Capital				
	Low (84 months)	Medium (96 months)	High (84 months)	High-Low	*p*-value
$v(\theta_{it}; \alpha_{jt}) – v(\theta_{it}; \alpha_j)$					
Low	0.315	1.671	0.644	0.329	0.713
2	0.330	1.451	0.923	0.593	0.446
3	0.627	1.575	0.779	0.152	0.841
4	0.795	1.235	0.804	0.009	0.990
5	-0.091	1.442	0.550	0.641	0.398
6	0.061	1.481	0.776	0.714	0.368
7	0.481	1.398	0.724	0.243	0.743
8	0.389	1.393	0.581	0.193	0.781
9	0.546	1.391	0.598	0.052	0.941
High	0.099	1.464	0.522	0.423	0.581
Low - High	0.216	0.207	0.122	-0.094	0.891
p-value	0.655	0.647	0.800		

TABLE A11 (Continued)

Panel E: Sort on long-run value to book ($v(\theta_{it};\ \alpha_j) - b_{it}$)

	Arbitrage Capital				
	Low (84 months)	Medium (96 months)	High (84 months)	High-Low	*p*-value
$v(\theta_{it};\ \alpha_j) - b_{it}$					
Low	0.419	1.235	0.726	0.307	0.671
2	0.437	1.197	0.919	0.482	0.466
3	-0.237	1.373	0.638	0.875	0.224
4	0.201	1.191	0.415	0.214	0.794
5	0.147	1.948	0.704	0.558	0.482
6	0.109	1.615	0.738	0.629	0.419
7	0.549	1.420	0.686	0.137	0.849
8	0.416	1.398	0.719	0.302	0.682
9	0.289	1.658	0.691	0.402	0.575
High	-0.018	1.846	0.640	0.658	0.383
Low - High	0.437	-0.611	0.086	-0.351	0.529
p-value	0.268	0.098	0.827		

This table presents average monthly returns of portfolios sorted on log market-to-book (or its components) conditional on arbitrage capital availability at portfolio formation, following Jylha and Suominen (2011) and Kokkonen and Suominen (2015). The time period is from Jul 1990 – Jun 2011. Each of the 22 portfolio formations for which data is available is classified into low, medium, or high arbitrage capital availability environment based on hedge funds assets under management in June of that year scaled by the average CRSP market capitalization over the previous 12 months. All monthly return observations until the next portfolio rebalancing are allocated to that category, resulting in three (approximately) equal-sized periods: low (84 months), medium (96 months), and high (84 months). Portfolio returns are value-weighted (VW). The time period is Jul 1990 – Jun 2012. Portfolios are formed every June 30 using NYSE breakpoints and rebalanced annually.

TABLE A12
Decomposition model estimated using per share values

Panel A: Portfolio sorts (RW)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it};\, \alpha_j)$	$m_{it} - v(\theta_{it};\, \alpha_{jt})$	$v(\theta_{it};\, \alpha_{jt}) - v(\theta_{it};\, \alpha_j)$	$v(\theta_{it};\, \alpha_j) - b_{it}$
Low	1.527	1.366	1.442	1.202	1.196
2	1.522	1.402	1.377	1.278	1.351
3	1.398	1.363	1.276	1.129	1.349
4	1.341	1.241	1.260	1.204	1.323
5	1.202	1.216	1.215	1.258	1.377
6	1.210	1.138	1.196	1.243	1.375
7	1.259	1.158	1.136	1.396	1.254
8	1.117	1.098	1.081	1.304	1.247
9	1.026	1.017	1.071	1.295	1.187
High	0.842	0.961	0.883	1.121	1.019
Low - High	0.685	0.404	0.559	0.081	0.176
t-stat	3.084	1.991	2.972	0.376	0.855
p-value	0.002	0.047	0.003	0.707	0.393
Annualized Sharpe Ratio	0.500	0.323	0.482	0.061	0.139
N	456	456	456	456	456

Panel B: Portfolio sorts (VW)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it};\, \alpha_j)$	$m_{it} - v(\theta_{it};\, \alpha_{jt})$	$v(\theta_{it};\, \alpha_{jt}) - v(\theta_{it};\, \alpha_j)$	$v(\theta_{it};\, \alpha_j) - b_{it}$
Low	1.455	1.249	1.351	1.174	1.125
2	1.227	1.325	1.202	1.158	1.003
3	1.179	1.281	1.271	1.096	1.030
4	0.941	1.126	1.157	0.975	0.974
5	1.155	1.215	1.153	1.033	1.096
6	1.101	1.017	1.065	0.979	1.196
7	1.028	1.028	1.041	1.101	1.078
8	1.079	0.945	0.972	0.989	0.910
9	0.975	0.992	1.032	1.081	0.945
High	0.905	0.914	0.870	0.854	0.968
Low - High	0.550	0.335	0.481	0.321	0.157
t-stat	2.649	1.707	2.753	1.499	0.925
p-value	0.008	0.089	0.006	0.135	0.355
Annualized Sharpe Ratio	0.430	0.277	0.447	0.243	0.150
N	456	456	456	456	456

Panel C: Firm-level return regressions

	1	2
Intercept	3.088	3.062
	0.000	0.000
First decomposition		
$m_{it} – v(\theta_{it}; \alpha_j)$	-0.479	
	0.000	
$v(\theta_{it}; \alpha_j) – b_{it}$	-0.091	
	0.313	
Comprehensive decomposition		
$m_{it} – v(\theta_{it}; \alpha_{jt})$		-0.506
		0.000
$v(\theta_{it}; \alpha_{jt}) – v(\theta_{it}; \alpha_j)$		-0.537
		0.103
$v(\theta_{it}; \alpha_j) – b_{it}$		-0.096
		0.289
Controls: m, β^{+}_{post}, β^{-}_{post}, $IVol_{post}$, *Illiquidity*, $Ret^{-2\text{-}12}$, Ret^{-1}, *OP*, *Inv*		
Adj. R^2	0.080	0.082
N	456	456

The table reports the results of portfolios sort tests (Panels A and B) and firm-level return regressions with all control variables (Panel C) when the decomposition model in equation (4) is estimated using per share values of market value of equity, book value of equity, and net income. To prevent the log transformations of values close to zero becoming influential observations, we use log of (1 + share price), log of (1 + book value per share), and log of (1 + abs (earnings per share)) when estimating the decomposition model. Portfolio returns are prior gross return weighted (RW) in Panel A and value-weighted (VW) in Panel B. Regressions are prior gross return weighted (RW) in Panel C. All variables are defined in Appendix A of the paper.

TABLE A13

Fama-French 30 industry classification (21 industries remain)

Panel A: Portfolio sorts (RW)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it};\ \alpha_j)$	$m_{it} - v(\theta_{it};\ \alpha_{jt})$	$v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$	$v(\theta_{it};\ \alpha_j) - b_{it}$
Low	1.522	1.525	1.580	1.080	1.262
2	1.554	1.444	1.415	1.393	1.224
3	1.413	1.436	1.450	1.295	1.241
4	1.377	1.353	1.306	1.319	1.232
5	1.266	1.232	1.219	1.250	1.268
6	1.271	1.191	1.237	1.231	1.309
7	1.289	1.097	1.184	1.220	1.311
8	1.181	1.095	1.094	1.253	1.301
9	1.116	0.979	0.941	1.261	1.269
High	0.781	0.803	0.755	1.029	1.078
Low - High	0.741	0.722	0.825	0.051	0.184
t-stat	3.539	4.111	5.413	0.275	1.050
p-value	0.000	0.000	0.000	0.784	0.294
Annualized Sharpe Ratio	0.574	0.667	0.878	0.045	0.170
N	456	456	456	456	456

Panel B: Portfolio sorts (VW)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it};\ \alpha_j)$	$m_{it} - v(\theta_{it};\ \alpha_{jt})$	$v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$	$v(\theta_{it};\ \alpha_j) - b_{it}$
Low	1.456	1.367	1.323	1.163	1.043
2	1.259	1.212	1.188	1.037	1.081
3	1.169	1.321	1.263	1.131	1.033
4	0.954	1.201	1.186	1.158	0.878
5	1.153	1.054	1.222	1.003	1.123
6	1.085	1.046	0.980	0.943	0.998
7	0.999	0.913	0.950	1.191	1.119
8	1.037	0.978	1.033	0.899	1.064
9	0.999	0.911	0.969	1.024	1.145
High	0.907	0.911	0.850	1.080	0.911
Low - High	0.549	0.456	0.472	0.084	0.131
t-stat	2.556	2.260	2.714	0.410	0.764
p-value	0.011	0.024	0.007	0.682	0.445
Annualized Sharpe Ratio	0.415	0.367	0.440	0.066	0.124
N	456	456	456	456	456

Panel C: Firm-level return regressions

	1	2
Intercept	2.912	2.813
	0.000	0.000
First decomposition		
$m_{it} – v(\theta_{it}; \alpha_j)$	-0.392	
	0.000	
$v(\theta_{it}; \alpha_j) – b_{it}$	-0.087	
	0.236	
Comprehensive decomposition		
$m_{it} – v(\theta_{it}; \alpha_{jt})$		-0.414
		0.000
$v(\theta_{it}; \alpha_{jt}) – v(\theta_{it}; \alpha_j)$		-0.326
		0.067
$v(\theta_{it}; \alpha_j) – b_{it}$		-0.048
		0.524
Controls: m, β^{+}_{post}, β^{-}_{post}, $IVol_{post}$, *Illiquidity*, $Ret^{-2\text{-}12}$, Ret^{-1}, *OP*, *Inv*		
Adj. R^2	0.079	0.081
N	456	456

The table reports the results of portfolios sort tests (Panels A and B) and firm-level return regressions with all control variables (Panel C) when the decomposition model in equation (4) is estimated using the Fama-French 30 industry classification (21 industries have a sufficient number of firms in each year). Portfolio returns are prior gross return weighted (RW) in Panel A and value-weighted (VW) in Panel B. Regressions are prior gross return weighted (RW) in Panel C. All variables are defined in Appendix A of the paper.

TABLE A14
Fama-French 38 industry classification (14 industries remain)

Panel A: Portfolio sorts (RW)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it};\ \alpha_j)$	$m_{it} - v(\theta_{it};\ \alpha_{jt})$	$v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$	$v(\theta_{it};\ \alpha_j) - b_{it}$
Low	1.625	1.523	1.576	1.092	1.347
2	1.504	1.544	1.487	1.343	1.299
3	1.389	1.448	1.462	1.420	1.150
4	1.380	1.384	1.283	1.374	1.224
5	1.265	1.209	1.324	1.308	1.326
6	1.336	1.164	1.157	1.240	1.325
7	1.258	1.075	1.135	1.175	1.296
8	1.257	1.093	1.087	1.167	1.280
9	1.114	1.004	1.026	1.235	1.283
High	0.764	0.825	0.775	0.956	1.106
Low - High	0.861	0.698	0.801	0.136	0.240
t-stat	4.062	3.878	5.015	0.708	1.322
p-value	0.000	0.000	0.000	0.479	0.187
Annualized Sharpe Ratio	0.659	0.629	0.813	0.115	0.214
N	456	456	456	456	456

Panel B: Portfolio sorts (VW)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it};\ \alpha_j)$	$m_{it} - v(\theta_{it};\ \alpha_{jt})$	$v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$	$v(\theta_{it};\ \alpha_j) - b_{it}$
Low	1.562	1.254	1.430	0.974	1.115
2	1.221	1.481	1.142	1.275	1.107
3	1.198	1.293	1.225	1.263	0.906
4	1.085	1.272	1.326	1.247	0.825
5	1.141	1.106	1.144	1.117	1.029
6	1.105	0.995	0.990	1.015	1.207
7	1.071	1.011	0.984	1.032	1.180
8	1.130	1.055	0.964	1.071	1.103
9	1.019	0.884	0.941	1.070	1.133
High	0.913	0.950	0.965	0.919	0.905
Low - High	0.649	0.304	0.465	0.055	0.210
t-stat	2.878	1.510	2.674	0.238	1.253
p-value	0.004	0.132	0.008	0.812	0.211
Annualized Sharpe Ratio	0.467	0.245	0.434	0.039	0.203
N	456	456	456	456	456

Panel C: Firm-level return regressions

	1	2
Intercept	2.951	2.838
	0.000	0.000
First decomposition		
$m_{it} – v(\theta_{it}; \alpha_j)$	-0.377	
	0.000	
$v(\theta_{it}; \alpha_j) – b_{it}$	-0.153	
	0.042	
Comprehensive decomposition		
$m_{it} – v(\theta_{it}; \alpha_{jt})$		-0.387
		0.000
$v(\theta_{it}; \alpha_{jt}) – v(\theta_{it}; \alpha_j)$		-0.702
		0.002
$v(\theta_{it}; \alpha_j) – b_{it}$		-0.118
		0.132
Controls: m, β^{+}_{post}, β^{-}_{post}, $IVol_{post}$, *Illiquidity*, $Ret^{2\text{-}12}$, Ret^{1}, *OP*, *Inv*		
Adj. R^2	0.082	0.084
N	456	456

This table reports the results of portfolios sort tests (Panels A and B) and firm-level return regressions with all control variables (Panel C) when the decomposition model in equation (4) is estimated using the Fama-French 38 industry classification (14 industries have a sufficient number of firms in each year). Portfolio returns are prior gross return weighted (RW) in Panel A and value-weighted (VW) in Panel B. Regressions are prior gross return weighted (RW) in Panel C. All variables are defined in Appendix A of the paper.

TABLE A15
Campbell (1996) 12 industry classification (11 industries after excluding finance)

Panel A: Portfolio sorts (RW)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it};\ \alpha_j)$	$m_{it} - v(\theta_{it};\ \alpha_{jt})$	$v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$	$v(\theta_{it};\ \alpha_j) - b_{it}$
Low	1.541	1.519	1.548	1.093	1.277
2	1.532	1.489	1.501	1.414	1.204
3	1.422	1.476	1.429	1.358	1.250
4	1.357	1.328	1.300	1.217	1.280
5	1.274	1.297	1.268	1.336	1.315
6	1.304	1.115	1.204	1.375	1.332
7	1.290	1.156	1.155	1.205	1.288
8	1.183	1.077	1.074	1.194	1.244
9	1.108	1.009	1.029	1.178	1.292
High	0.789	0.817	0.779	0.976	1.122
Low - High	0.752	0.702	0.770	0.117	0.155
t-stat	3.601	3.762	4.480	0.616	0.956
p-value	0.000	0.000	0.000	0.538	0.340
Annualized Sharpe Ratio	0.584	0.610	0.727	0.100	0.155
N	456	456	456	456	456

Panel B: Portfolio sorts (VW)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it};\ \alpha_j)$	$m_{it} - v(\theta_{it};\ \alpha_{jt})$	$v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$	$v(\theta_{it};\ \alpha_j) - b_{it}$
Low	1.482	1.287	1.305	1.059	1.064
2	1.251	1.415	1.309	1.142	1.026
3	1.183	1.419	1.268	1.189	0.910
4	0.955	1.213	1.186	1.158	0.987
5	1.147	1.193	1.150	1.173	1.205
6	1.139	0.979	1.097	1.116	1.147
7	1.060	1.084	1.072	0.994	1.154
8	1.098	0.949	1.060	1.038	1.086
9	0.964	0.987	0.994	0.976	1.082
High	0.918	0.881	0.869	1.041	0.949
Low - High	0.564	0.405	0.436	0.018	0.115
t-stat	2.628	1.909	2.422	0.088	0.732
p-value	0.009	0.057	0.016	0.930	0.464
Annualized Sharpe Ratio	0.426	0.310	0.393	0.014	0.119
N	456	456	456	456	456

Panel C: Firm-level return regressions

	1	2
Intercept	2.895	2.803
	0.000	0.000
First decomposition		
$m_{it} - v(\theta_{it}; \alpha_j)$	-0.329	
	0.000	
$v(\theta_{it}; \alpha_j) - b_{it}$	-0.140	
	0.047	
Comprehensive decomposition		
$m_{it} - v(\theta_{it}; \alpha_{jt})$		-0.338
		0.000
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$		-0.348
		0.149
$v(\theta_{it}; \alpha_j) - b_{it}$		-0.102
		0.165
Controls: m, β^{+}_{post}, β^{-}_{post}, $IVol_{post}$, *Illiquidity*, $Ret^{-2\text{-}12}$, Ret^{-1}, *OP*, *Inv*		
Adj. R^2	0.080	0.082
N	456	456

This table reports the results of portfolios sort tests (Panels A and B) and firm-level return regressions with all control variables (Panel C) when the decomposition model in equation (4) is estimated using Campbell (1996) 12 industry classification (11 industries after excluding finance). Portfolio returns are prior gross return weighted (RW) in Panel A and value-weighted (VW) in Panel B. Regressions are prior gross return weighted (RW) in Panel C. All variables are defined in Appendix A of the paper.

TABLE A16
Augmenting the valuation model with growth

Panel A: Portfolio sorts (RW)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it};\ \alpha_j)$	$m_{it} - v(\theta_{it};\ \alpha_{jt})$	$v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$	$v(\theta_{it};\ \alpha_j) - b_{it}$
Low	1.579	1.504	1.548	1.218	1.329
2	1.547	1.496	1.500	1.302	1.344
3	1.434	1.504	1.402	1.358	1.274
4	1.421	1.355	1.419	1.288	1.293
5	1.300	1.391	1.349	1.346	1.410
6	1.346	1.206	1.288	1.358	1.325
7	1.318	1.179	1.261	1.353	1.311
8	1.219	1.211	1.125	1.343	1.363
9	1.155	1.113	1.095	1.216	1.307
High	0.878	0.873	0.847	1.133	1.123
Low - High	0.701	0.630	0.701	0.085	0.206
t-stat	3.353	3.782	4.794	0.448	1.147
p-value	0.001	0.000	0.000	0.654	0.252
Annualized Sharpe Ratio	0.544	0.614	0.778	0.073	0.186
N	456	456	456	456	456

Panel B: Portfolio sorts (VW)

	$m_{it} - b_{it}$	$m_{it} - v(\theta_{it};\ \alpha_j)$	$m_{it} - v(\theta_{it};\ \alpha_{jt})$	$v(\theta_{it};\ \alpha_{jt}) - v(\theta_{it};\ \alpha_j)$	$v(\theta_{it};\ \alpha_j) - b_{it}$
Low	1.457	1.320	1.263	0.993	1.119
2	1.247	1.316	1.160	1.073	1.059
3	1.195	1.218	1.201	1.087	0.975
4	0.966	1.219	1.303	1.006	0.982
5	1.168	1.078	1.168	1.064	1.058
6	1.101	0.989	1.000	1.170	1.071
7	1.047	1.035	1.076	1.222	1.020
8	1.078	1.010	0.935	1.042	1.106
9	1.005	0.943	0.964	1.036	1.008
High	0.903	0.921	0.934	1.001	0.987
Low - High	0.554	0.398	0.328	-0.008	0.131
t-stat	2.633	1.992	1.979	-0.042	0.757
p-value	0.009	0.047	0.048	0.966	0.449
Annualized Sharpe Ratio	0.427	0.323	0.321	-0.007	0.123
N	456	456	456	456	456

Panel C: Firm-level return regressions

	1	2
Intercept	2.626	2.605
	0.000	0.000
First decomposition		
$m_{it} - v(\theta_{it}; \alpha_j)$	-0.353	
	0.000	
$v(\theta_{it}; \alpha_j) - b_{it}$	-0.093	
	0.247	
Comprehensive decomposition		
$m_{it} - v(\theta_{it}; \alpha_{jt})$		-0.360
		0.000
$v(\theta_{it}; \alpha_{jt}) - v(\theta_{it}; \alpha_j)$		-0.186
		0.403
$v(\theta_{it}; \alpha_j) - b_{it}$		-0.049
		0.552
Controls: m, β^{+}_{post}, β^{-}_{post}, $IVol_{post}$, *Illiquidity*, $Ret^{-2\text{-}12}$, Ret^{-1}, *OP*, *Inv*		
Adj. R^2	0.800	0.081
N	456	456

This table reports the results of portfolios sort tests (Panels A and B) and firm-level return regressions with all the control variables (Panel C) when the decomposition model in equation (4) is augmented with a firm-level measure of growth, computed as sales growth over the period from *t* to *t*-3. Portfolio returns are prior gross return weighted (RW) in Panel A and value-weighted (VW) in Panel B. Regressions are prior gross return weighted (RW) in Panel C. All variables are defined in Appendix A of the paper.