# Disclosure complexity, quality investing and equity returns

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**Abstract**

This study finds a significantly negative cross-sectional relationship between document disclosure complexity of 10-K and future stock returns. We provide a behavioral explanation to our results based on the idea that investors underweight signals indicating higher quality or lower disclosure complexity resulting in mispricing. Using eXtensible Business Reporting Language (XBRL) as a proxy for document complexity we find that firms with lower (higher) disclosure complexity earn higher (lower) annualized abnormal returns ranging from 9.2% to 12.8%. We find that the complexity return is stronger for small-cap growth stocks, and investing in the low-high complexity portfolio substantially increases the portfolio Sharpe ratios, ranging from 20% to 63%. Furthermore, institutional ownership and industry complexity are plausible channels for this negative relationship between disclosure complexity and stock returns. We also perform extensive tests to rule out the possibility of the premia being a part of the "factor zoo".

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## 1. Introduction

Annual 10-K filings provide key disclosures about a company's financial position, performance, risks, and governance. These disclosures aim to reduce information asymmetry between managers and external stakeholders including investors, creditors, regulators, and analysts. However, the sheer length and complexity of 10-K filings, which routinely exceed 100 pages, raises challenges for efficient information extraction and synthesis obscuring transparency and hampering the monitoring of firms.

Previous research has mostly used textual analysis to examine the market response or stock price momentum to positive or negative news and fundamental information (Boudoukh, Feldman, Kogan, and Richardson, 2019), article tone in media coverage or earnings press releases (Hillert, Jacobs, and Muller, 2014; Huang, Teoh, and Zhang, 2014), or creating a comprehensive manager sentiment index based on the aggregated textual tone of corporate financial disclosures (Jiang, Lee, Martin, and Zhou, 2019). Bushee, Gow, and Taylor (2018) examine the impact of language complexity employed in firms' quarterly earnings calls. Jegadeesh and Wu (2013) develop an alternate word/tonal classification methodology to better predict risk and return or improve the current understanding of the dominant sentiment emerging from 10-Ks (see Calomiris and Mamaysky, 2019; Azimi and Agrawal, 2021). Hwang and Kim (2017) examine document readability identified through copyediting software and its impact on the traded price of closed-end investment companies.

Another stream of research examines the extent of firms' financial constraints by parsing the 10-Ks and identifying "constraining" words with an appropriate lexicon or through a textual analysis of the "management discussion and analysis" section of 10-Ks using a naïve Bayesian algorithm popular in computational linguistics (Bodnaruk, Loughran, and McDonald, 2015; Buehlmaier and Whited, 2018). Furthermore, Cohen, Malloy, and Nguyen (2020) examine the history of *changes* in the language and construction of annual filings of U.S.-based firms. The authors infer that 10-Ks may have become less informative over time due to their increasingly complex nature, which leads investors to miss subtle signals from changes and adjustments in these documents relative to their initial version.[1]

In this study, we extend the above arguments to investigate whether disclosure complexity in 10-K documents plays a significant role in determining the cross-section of future stock returns. Our motivation stems from the theoretical underpinnings rooted in impression management (IM) and obfuscation theories (OT) along with investor behavioral theories. Specifically, impression management theory suggests that managers craft their communications to influence stakeholders' perceptions positively (Bolino, Kacmar, Turnley & Gilstrap, 2008). This theory posits that clear and readable disclosures can enhance investor confidence and trust by facilitating better comprehension and

[1] In the accounting literature, there is a vibrant research steam centered on the issues of the tone (including linguistic tone and change in tone) and readability of the underlying documents related to corporate communications involving the MD&A section of the 10-Ks, 8-Ks, quarterly earnings calls, media coverage among others and their impact of stock prices, returns and other observable firm transactional measures (see, for example, Kravart and Muslu, 2013; Segal and Segal, 2016; Chen, Nagar and Schoenfeld, 2018; Campbell, Lee, Lu and Steele, 2020; D'Augusta and DeAngelis, 2020; Wang, 2021; Chahine, Colak, Hasan and Mazboudi, 2020).

reducing uncertainty (Bradac, Bowers & Courtright, 1979; Larrimore et al., 2011). Conversely, obfuscation theory argues that managers might deliberately obscure information to conceal adverse performance or prospects (Li, 2008). Evidence also suggest that managers might opportunistically obfuscate via complex filings (Li, 2008; Lo, Ramos, and Rogo, 2017; Loughran and McDonald, 2014) while other studies argue that firms with complex 10-Ks might simply require greater XBRL tags to accurately convey the underlying intricacy of their business (Cohen, Malloy and Nguyen, 2020; Efendi, Srivastava, and Swanson, 2007). Regardless, document complexity to quantify the relative 10-K complexity appears worthy of further investigation. An important, question is whether XBRL tag density in a 10-K filing plays a significant role in determining the stock returns. Its importance lies in being able to address the ongoing debate on the transparency-related trade-offs of mandatory financial disclosures (Cohen et al. 2020). If high complexity is associated with higher borrowing costs or lower valuations, it suggests obfuscation raises stakeholders' information risk premiums (Lo et al. 2017) which, in turn, underscores the need for tighter regulation or simplification in disclosing firm's annual documents. However, a positive relationship between XBRL tags and future returns may indicate that relatively less complex (or easy-to-understand) disclosures reduce information asymmetry.

Rational asset pricing models predict that stocks with greater risk carry higher return premiums ('risk view') (see Black, Jensen, and Scholes, 1972; Fama and MacBeth, 1973; Gibbons, 1982; Stambaugh, 1982 among other recent studies). In our context, this would mean that firms with higher complexity would be anticipated to have lower prices in compensation for higher information asymmetry and higher monitoring costs. Consequently, one would expect higher returns from stocks with higher document complexity. We test this assumption and document a contradicting conclusion, where we find a negative cross-sectional relationship between document disclosure complexity of 10-K and future stock returns. We explain our results based on the stream of literature that shows that certain assets deemed riskier by standard models display predictably low expected returns (see for example, Haugen and Heins, 1975; Haugen and Baker, 1991; Ang, Xing, and Zhang.,2009; Clarke, Silva, and Thorley, 2006, 2011; Blitz and van Vliet, 2007; Baker, Bradley, and Wurgler, 2011, among others). These studies imply that lower-risk assets earn higher returns contrary to conventional asset pricing models. For example, the 'quality anomaly' has been documented to be highly profitable when investors go long (short) on high (low) quality stocks (Asness, Frazzini and Pedersen, 2019 and Novy-Marx, 2013). The underlying intuition is that investors underweight certain signals that could indicate higher quality but are too focused on other indicators like volatility, momentum, etc. Therefore, suggesting that factor premia may also arise because of behavioural biases including mispricing and many other frictions ('behavioral view').

In our context, we use the 10-K document complexity as a signal of quality that captures several aspects of a firm including information asymmetry, monitoring costs and investor confidence. On economic grounds, we expect to see future returns to be negatively correlated with document complexity if indeed it is driven by mispricing. For example, firms that have 10-K documents with a lower proportion of complexity provide a higher degree of certainty that pushes up the future valuations, on the contrary firms that display higher complexity are overpriced because investors cannot fully incorporate the fundamentals in their information sets, consequently, have lower investor confidence. Therefore, we argue that investors prefer less complex portfolios is that such portfolios contain higher quality stocks, and such stocks are underpriced.

Based on the above discussion, we create *complexity* portfolios constructed on the XBRL characters contained in firms' annual 10-K filings following a similar approach as Fama-French (1992; 1996; 2015; 2016), Novy-Marx (2014), and Asness, Frazzini and Pedersen (2019) among other studies to determine the relationship between disclosure complexity and expected stock returns. Briefly, we first sort stocks annually into five quintile portfolios (Q1 through Q5) or decile (D1 through D10) based on the 10-K XBRL or HTML (HyperText Markup Language) characters from 1994 through 2021 to capture the document complexity.[2] Notably, we use HTML characters for the years 1994 through 2011 since XBRL was made mandatory only after 2012. However, the SEC encouraged the companies to voluntarily submit under XBRL from 2004. We also note that HTML and XBRL are both machine-readable formats and comparable technologies for reporting. Therefore, should capture the reporting complexity qualitatively similar. The lowest (highest) quintile portfolio contains firms with fewer (greater) XBRL/HTML characters. We identify the lowest (highest) quintile portfolio as '*Easy*' ('*Complex*'). Then we compute the monthly value-weighted portfolio returns of each of the quintile (or decile) portfolios based on its *t+2* month's returns, where *t* is the month of a specific 10-K filing. Finally, we compute the *low-high* portfolio returns, by going long in the *Easy* portfolio (Q1 or D1) and going short in the *Complex* portfolio (Q5 or D10).

We begin by observing that the portfolio excess returns are higher for the portfolios with relatively fewer XBRL tags, suggesting that investors prefer to hold stocks that have lower reporting complexity. Building on these initial findings, we regress these *complexity*-based portfolio returns on the well-known risk factors (first the Fama-French five factors and then the more recent *q*-factors). We find that a *low-high* portfolio yields an average annual risk premium of 9.1% to 12.8%, depending on how the stocks are sorted. While the exact magnitude of document complexity-related risk premiums in a self-financed low-high portfolio or the long-only portfolios could be debated ad nauseum, there is little doubt that the *complexity*-driven risk premiums are statistically, and economically, significant. Subsequently, we also test the impact of document complexity on stock returns in double-sorted portfolios on Size (SIZE) - *complexity* and book-to-market (BM)- *complexity*, which captures fundamental firm characteristics. We find the strongest *low-high* returns are for the small-cap and growth stocks and the lowest *low-high* returns are for the large-cap and value stocks. We attribute the results from double-sorted premiums to previous research that has shown that both firm size and its

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book-to-market ratio are proxies for pervasive stock-specific risk (Chen, Chang, Yu, and Mayes, 2005; Jegadeesh and Wu, 2013). Also, in a series of influential papers, Fama and French (1992; 1996; 2015; 2016) show that risk factors like firm size and firms' book-to-market ratio significantly explain stock returns, with smaller firms posing higher risk, and firms with lower book-to-market ratio (i.e., growth stocks) posing higher risk than firms with higher book-to-market ratio (i.e., value stocks). Given the higher inherent risk of small companies, stakeholders of such companies will pay particular importance to the 10-Ks. This implies that small firms with 10-Ks with lower complexity are associated with positive investor reactions. In contrast, we expect the relationship between complexity and investor reaction to weaken for larger firms because larger firms tend to have more information in their 10-K documents (Li, 2008) disclose 'more' redundant information through footnotes and tend to repeat disclosures across various sections because of their operational complexity (Cazier and Pfeiffer, 2016).

Furthermore, we examine the plausible channels of complexity premiums and find that stocks with lower institutional ownership and stocks in industries that have systematically higher accounting complexity carry higher premiums. We do so by estimating the *low-high* returns for portfolios of high and low institutional ownership obtained from the 13-F holdings data. Similarly, we estimate the *low-high* returns for each of the 12 Fama-French industry classifications. We find that industries such as healthcare, mining, and wholesale services industry earn a significantly positive *low-high* monthly alpha.

Finally, we also estimate individual stock-level regressions following the classical Fama-McBeth approach and then using panel fixed effect regressions with clustered standard errors as recommended by Petersen (2009). Our results are consistent with our main findings even in the stock-level regressions. Lastly, to rule out the possibility of document complexity factor as merely another factor in the 'factor zoo' we conduct a battery of tests. Indeed, the risk premium survives the spanning tests, tangency portfolio test, and factor-mimicking portfolio tests. Our study contributes to the literature by being the first to demonstrate that a risk factor based on document complexity may capture significant abnormal returns even after controlling for prominent risk factors and transaction costs.

The rest of the paper proceeds as follows: Section 2 describes the data sources and defines our portfolio construction, Section 3 presents the summary statistics and the main results, and Section 4 explores the plausible channels for the return premium. Section 5 discusses the factor zoo problem and presents various robustness tests, and Section 6 presents the stock-level regressions and Section 7 provides our concluding remarks.

## 2. Data

For our analyses, we utilize the firms listed on NYSE, AMEX, and NASDAQ with share codes 10 and 11 on CRSP (i.e., only common stocks) for the years January 1994 through December 2021. The original sample includes 203,934 10-K filings involving an average of 9,280 firms over 28 years.

Second, we obtain the monthly Fama and French (2015) factors, NYSE size (*SIZE*), and book-to-market (*BM*) breakpoints from Ken French's website. Similarly, the *q5* factors from the q group's website, *SY-4* factors from Robert Stambaugh's website, Barillas and Shanken (2018) – *BS-6* factors from AQR Capital website, and finally the factor clusters from Brian Kelly's website. We obtain the complexity measures from the SeekEdgar database and Prof. Tim Lougran's website.[3] SeekEdgar LLC provides the annual readability measures for all firms that file their 10-K with the SEC. We obtain monthly stock returns, index returns, and market values from CRSP and accounting information, such as annual book values and shares outstanding, from the COMPUSTAT Annual Fundamental files.

Finally, consistent with prior studies (Jegadeesh and Wu, 2013; Loughran and McDonald, 2011), we employ the following rules to construct the final sample for analysis.

- We consider only the initial 10-K filing in a given year by a given firm. In other words, we exclude subsequent amendments to the initial 10-K filed by many firms over the year since most information is reported in the initial filing.
- Since SEC EDGAR identifies the firms through Central Index Key (CIK), we use the WRDS CRSP-COMPUSTAT database to match the CIKs in EDGAR and WRDS. Thus, we exclude all firms for which we cannot match CIKs between the two databases.
- Our analyses use various accounting and financial variables such as market capitalization and stock returns from CRSP monthly file. We exclude all firms for which such data are not available.[4]

Since our criteria require matching firms from SEC with CRSP and COMPUSTAT our final sample yields to 59,467 firm-year observations. In the final count, we obtain 464,560 firm-month observations involving 8,385 distinct firms (the average of 2,050 firms every year) between 1994–2021 (both years included). We should note that, by comparison, Jegadeesh and Wu (2013) report a final sample of 45,860 firm-year observations for the sample period 1995–2010. Loughran and McDonald (2011) use a sample of 44,822 observations, and Bodnaruk, Loughran, and McDonald report a sample size of 51,533 for the period 1996–2011.

### ***2.1. Constructing complexity portfolios through XBRL***

We construct the *complexity* portfolios through the natural logarithm of the number of XBRL characters in each 10-K document. Since XBRL characters are available from 2012 we use HTML characters for the years 1994 through 2011. Specifically, we sort stocks based on the 10-K XBRL or

[3] The FF-5 factors are available on: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research. The q5 factors are available on: https://global-q.org/factors.html. The *SY-4* factors are available on: https://finance.wharton.upenn.edu/~stambaug/. The *BS-6* factors are available on: https://www.aqr.com/Insights/Datasets/The-Devil-in-HMLs-Details-Factors-Monthly. The HTML characters is available on: https://sraf.nd.edu/loughranmcdonald-master-dictionary/. Finally, the factor themes are available on: https://jkpfactors.com/.

[4] Our results remain (overall stronger) when we exclude micro-cap stocks. The results are available upon request.

HTML characters every year from 1994 through 2021 and classify the stocks into five approximate quintile groups: namely Q1, Q2, Q3, Q4, and Q5, following the methodology of Fama and French (1993, 2015) and prior studies. Stocks in Q1 (Q5) have the lowest (highest) *XBRL* characters. The top quintile (Q5) stocks are identified as (*Complex*), and the bottom quintile (Q1) stocks are identified as (*Easy*). Next, we compute the monthly value-weighted returns of each of the quintile portfolios following the 10-K filing month. To avoid any confounding effects from investor over or under-reaction to 10-K filings or overlapping economic events during or immediately after the filings, we consider the *t+2* month's returns for each stock, rather than the filing month (*t*) or the immediate next month (*t+1*).[5] This procedure yields five monthly return series over 335 months for the Q1 through Q5 portfolios respectively. Finally, we compute the *low-high* (*Easy – Complex*) portfolio returns by going long in the lowest complexity (or *Easy*) portfolio (Q1) and going short in the highest complexity or (*Complex*) portfolio (Q5).

# 3. Results

## *3.1. Summary Statistics*

Table 1 shows the summary statistics of the study's sample. The average (median) size of the sample firms, captured by *SIZE*, over the sample period, is \$3.8 billion (\$519 million), indicating that the average stock in our sample is a mid-capitalization according to the market capitalization cut-offs from Financial Industry Regulatory Authority (FINRA).[6] The left skewness demonstrates that small-sized firms outnumber large firms in the dataset.[7] The mean (median) *BM* of firms is 0.63 (0.47). In comparison, Buehlmaier and Whited (2018) report an average *BM* of 0.35 in their 1994–2010 sample. Additionally, Aswath Damodaran's website provides the *BM* distributional statistics of publicly traded companies in the U.S. as of January 2021, and the reported mean BM is 0.21.[8] Our sample appears to have a relatively higher proportion of undervalued companies. Additionally, from Table 1 we find that the average operating profitability (*OP*) and investments (*Inv*) are 0.25 and -0.09 respectively. We define these two measures consistent with Fama and French (2015), where *OP* is defined as revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense all divided by book equity. Similarly, *Inv* is defined as the change in total assets from the fiscal year ending in year *t-2* to the fiscal year ending in *t-1*, divided by *t-2* total assets.[9] Table 1 also shows that

[5] Our results are qualitatively similar, in significance when we consider (*t+1*) month returns.
[6] FINRA provides the suggestive range for market capitalization classification under this article: https://www.finra.org/investors/insights/market-cap
[7] According to Businessinsider.com, the NYSE has over 2,400 companies that collectively account for over \$21 trillion in market cap. NASDAQ comprises more listed companies than the NYSE but has a wider dispersion of company size. The NASDAQ is dominated by the behemoths like Apple, Microsoft, Amazon, Alphabet, Tesla, and Facebook, which account for well over \$8 trillion in market cap.
[8] The data can be found here: https://pages.stern.nyu.edu/~adamodar/
[9] OP is calculated through the Compustat data items [SALE - (COGS - XSGA - XINT)] divided by BE [BE = sum (AT, -LT, -PSTKL, TXDITC, DCVT]. We operationalized *Inv* through the Compustat data item = 6 (item name is AT).

the average number of words per 10-K document over our sample period is 43,049. Firms in our sample have an average of 3.4 million XBRL characters and about 690,000 HTML characters, confirming the evidence by Cahan, Chang, Siqueira, and Tam (2022) that post-2012 the 10-K disclosures have increased substantially.

### *3.2. Univariate results*

We begin by examining the value-weighted and equal-weighted excess returns of the *complexity* portfolios. Panel A reports the monthly value-weighted and equal-weighted gross and net returns. Where the net returns are adjusted for S&P value-weighted index monthly returns. The last row represents the returns for the low-high (Easy – Complex) portfolios. From Panel A we find that the monthly returns for Q1 (*Easy*) portfolio is significantly higher than those of Q5 (*Complex*), where the returns for Q1 is 1.98% and 1.56% per month for the value-weighted and equal-weighted portfolios respectively on the gross basis. On the other hand, the value-weighted and equal-weighted portfolio returns for Q5 are 1.39% and 0.78% per month respectively on the net basis. We also find that the portfolio returns systematically decrease from Q1 to Q5 suggesting a lower (higher) monthly portfolio returns for most (least) complex stocks. More importantly, the value-weighted low-high returns earn a significant 0.63% per-month (7.8% annualized) returns. Similarly, Panel B reports the Daniel, Grinblatt, Titman and Wermers (DGTW, 1997) adjusted portfolio returns for each of the XBRL portfolio, not surprising the corresponding portfolio returns for the DGTW adjusted portfolios are lower than the gross returns in Panel A, however here too *Easy* portfolio earns a significantly higher returns relative to that of *Complex*. In Panel B we also find a significant return for the low-high value-weighted portfolio, that earns 0.73% per-month (9.12% annualized) returns. Overall, the results from Table 2 show that stocks in the *Easy* (*Complex*) portfolio earns a significantly higher (lower) monthly return. Thus, the results provide initial evidence to our central hypothesis that firms with lower document complexity outperform those with relatively higher document complexity.

Figure 1 provides a graphical representation of the monthly low-high returns, along with S&P 500 value-weighted monthly returns over the sample period. We observe a peak in *low-high* returns during 2000-01, the height of the dot-com era, coinciding with spike in S&P 500 returns. The *low-high* portfolio annual returns continued to spike around 2009 and 2019, before failing in early 2009 during the housing market collapse, finally dipping below the S&P 500 returns during 2020-21 at the peak of COVID-19 pandemic. Overall, we observe that the low-high returns coincide with the S&P 500 returns with a correlation of 0.11, however we find that the low-high returns have a lower return volatility compared to S&P 500 return volatility (3.2% versus 4.3%) and a higher Sharpe ratio (0.2 versus 0.18).

### *3.3. Baseline results.*

We examine whether the significant excess returns associated with *complexity* portfolios persist when we control for well-known risk factors. Table 3 presents the results from regressing the *XBRL*-sorted portfolios on the five Fama-French (*FF5*, 2015) factors, which are known to significantly explain the cross-section of stock returns. As discussed above, we sort on *XBRL* into quintile or decile portfolios by grouping stocks into *Easy* (Q1) and *Complex* (Q5 or D10) portfolios. We create a self-financing *low-high* portfolio where we go long on the *Easy* quintile portfolio and short on the *Complex* quintile portfolio. Our low-high strategy is driven by our reasoning that we have argued earlier that stocks with most XBRL indicate a more complex, less readable 10-K document because it contains more detailed and complex accounting information. Conversely, a lower frequency of XBRL characters might suggest a simpler, more readable 10-K disclosure.[10]

The results in Panel A, estimated over the entire sample period, indicate that the monthly alphas for the low-high quintile portfolio equals 0.617% (t-stat = 4.10) and implies that the risk-adjusted monthly returns (annualized to about 7.7%) are statistically significant at conventional levels. Furthermore, in columns 2 and 4 we augment momentum factor (*WML*) of Carhart (1997) to the *FF5* factors and we find that the *low-high* quintile portfolio alpha increases to 0.643 (t-stat = 4.21), that earns an annualized return of about 8%. Finally to ensure that the low-high returns are not driven by the portfolio sorting method, in columns 3 and 4 we report the low-high regressions based on decile sorts and re-define the *Easy* (Decile 1) and *Complex* (Decile 10), here too we find that the low-high alphas earn a significant monthly return of 0.80 (t-stat = 3.68) and 0.85 (t-stat = 3.68) respectively resulting in an annualized returns of 9.12% on a risk-adjusted basis. Notably, the alphas from the low-high portfolio are statistically and economically significant. The t-statistics for alphas under both the quintile and decile sorts clearly cross the threshold level of 3.0 recommended by Harvey, Liu and Zhu (2016).

We note, however, that since our sample includes the dot-com bubble period and the global financial crisis, our observed alphas could be skewed upward. To present a more realistic or balanced measure of the alphas we re-estimate our model after excluding the dot-com bubble period between June 1999 and July 2001 and December 2007 through June 2009 to account for global financial crisis in Panel B of Table 3. We find that the monthly excess return estimates have increased relative to our base-line alphas. Specifically, the monthly excess returns of the low-high portfolio display increase in monthly alphas both for the quintile and decile portfolios (0.73% compared to 0.61% and 0.9% compared to 0.64%). The statistical significance remains strong with a *t-stat* of 5 (above the 3.0 threshold). Interestingly, the magnitude of the alphas lies well within the range of those reported by other studies investigating innovations related to liquidity, adverse selection, firm capital structure, or other firm-specific risk characteristics.[11]

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[10] Additionally, Ertugrul, Lei, Qiu and Wan (2017) conclude that shareholders of firms with more ambiguous annual reports not only suffer from less information disclosure but also bear the increased cost of external financing. Campbell, Chen, Dhaliwal, Lu and Steele (2014) find that firms facing greater risks disclose more risk factors in their 10-K filings and that managers provide meaningful risk factor disclosures.

[11] For instance, Easely et al. (2010) report an approximate 13.5% annual excess return (1.04% monthly) in their extreme tercile PIN portfolio (Table 2). Jegadeesh and Titman (1993) find 9%–12% annual excess returns (0.7%–0.9% monthly) in their momentum portfolios. Buehlmeier and Whited (2018) report that a portfolio-based measure of firm financial constraints, constructed using textual analysis of firms' annual reports, earns an annualized risk adjusted excess return of approximately 6.5%. Additionally, we observe that a passive investment

In recent research, Harvey, Liu, and Zhu (HLZ, 2016) highlight the notion that widely used data such as stock returns in the U.S. are likely to produce asymptotic values of t-statistics that lead to unwarranted rejections of the null hypothesis. In other words, the results may appear statistically significant when they are not. Furthermore, they establish a standard for whether the returns associated with a given risk factor are *truly* significant by emphasizing that the *t-statistics* related to average returns should be above the critical value of 3.0. We note that the *t-statistics* associated with the intercept in all three long-only portfolios and the low-high portfolio are largely above the critical cut-off of 3.0. Specifically, we find that the t-stat of the alphas in the low-high portfolios reported in Column 1 under both Panel A and B are 4.10 and 5.0 respectively.

Regarding other risk factors in the regressions, we find that *SMB* is strongly significant, its impact appears to be subsumed primarily in *HML* which loads negatively. We also find that *RMW* and CMA loads negatively, although insignificant at conventional levels. Overall, the Fama-French risk factors appear to be controlling for the risks, more importantly except SMB other factors do not load significantly coupled with a significant alpha suggests that complexity risk is not subsumed by FF5 factors. Thus, the risk-adjusted returns in Table 3 confirm our initial findings from Table 2 that *XBRL* portfolio return remain significant and is not explained by other well-known risk factors.

### *3.4. Complexity* **versus** *SIZE* **and** *BM*

We now investigate whether the significant relationship between portfolio returns, and the *low-high Complexity* portfolio returns as documented above, holds up in different firm size percentiles. This examination is pertinent given that the relationship between firm size and stock returns is well documented going back at least four decades.[12] We annually double sort firms based first on *SIZE* into the top 30%, middle 40%, and the bottom 30%, based on the NYSE annual firm size breakpoints, and then on *Complexity* quintiles. Panel A of Table 4 provides the excess returns of the 6 long-only portfolios (Q1Small, Q1Medium, Q1Large; Q5Small, Q5Medium, Q5Large) and three low-high portfolios for each size classification. From Table 4 of Panel A, we find that the low-high returns are relatively higher (and statistically significant) in small sized firms relative to medium and large firms. Similarly, in Panel B we also perform a double sort of firms based on *BM* and *Complexity* using the NYSE annual *BM* breakpoints. This is done to tease out any potentially differential impact across growth and value stocks. From Panel B of Table 4, we see that the impact of *XBRL* on excess returns is significantly higher in the low *BM* (i.e., growth) portfolio compared to the high *BM* (i.e., value)

strategy of investing in S&P 500 index earns a CAGR of 7.4% annually (0.60% monthly) over a similar sample period similar to ours.

[12] For example, Banz (1981) showed that small firms stocks displayed on average higher risk adjusted returns than large firms' stocks. Reinganum (1981) confirmed that size-based portfolios displayed average returns systematically different from those predicted by the two-parameter CAPM (see, also, Rogers, 1988). And, last but not least, Fama and French (1993, 2015) showed that firm size is an important risk factor explaining average stock returns.

portfolio. Specifically, we find that the low-high returns for the low *BM* portfolio is 0.69% per month and is statistically significant (t-stat = 3.66) compared to 0.30% per month (t-stat = 2.1).

Collectively, from both panels, the emergent picture is that of low-high portfolio having the greatest impact on small-cap and growth stocks and the least impact on large-cap and value stocks. Examples of small-cap category stocks are John Wiley & Sons, 1-800-Flowers, Wabash National, Timberland, Eastman Kodak, etc. Stocks that fit the bill in the large- cap-value group are companies like Coca Cola, Cisco Systems, General Electric, and Walmart.[13]

### 3.5. *Double sorts based on Size-Complexity and BM-Complexity*

We, next, examine if the patterns revealed between the excess returns and complexity portfolios in Table 4 also hold on a risk adjusted basis – especially along *SIZE* and *BM* sorts. We present results pertaining to the low-high portfolios (i.e., long on *Easy* or Q1 portfolio and short on *Complex* or Q5 portfolio) and examine their performance within different firm size partitions. Table 5 reports the regression for the double sorted portfolios. In Panel A, we regress the low-high returns on the *FF5* factors for each S*IZE* breakpoints. The annualized risk adjusted returns captured by the regression alphas for the small and medium size portfolios, are 12.95% (*t-stat* = 6.16) and 10.30% (*t-stat*= 5.29), respectively. We also confirm that, within each *SIZE* category, the majority of the returns come from the long side of the strategy (i.e., Q1 portfolio). Furthermore, our alphas also comfortably clear the hurdle of *t-stat* = 3.0 set by HLZ. While the *Large* portfolio earns a relatively lower risk-adjusted alpha of 7% (*t-stat* = 3.31). Similarly, from Panel B of Table 5 we also find that the value stocks earn a significantly high alpha of 10.03% (*t-stat* = 5.32) compared to growth stocks with an alpha of 4.66% (*t-stat* = 2.10). Overall, from Table 5 we find that the *Complexity* premium is significant in our bi-variate portfolios suggesting that document complexity related risk premium cannot be explained by significant firm characteristics.

### 3.6. *Controlling for q5 factors*

Hou, Xue and Zhang (HXZ, 2015) construct a new empirical model that, they contend, largely summarizes the cross section of average stock returns. Their *q*-factor model is built on the *q*-theory of investment, where the expected return of an asset in excess of the risk-free rate, denoted $E[r_i] - r_f$, is described by the sensitivities of its returns to 4 factors: the market excess return (*MKT*); the difference between the return on a portfolio of small size stocks and the return on a portfolio of large size stocks ($r_{ME}$, *ME*), the difference between the return on a portfolio of low investment stocks and the return on a portfolio of high investment stocks ($r_{I/A}$, *IA*), and the difference between the return on a portfolio of high profitability stocks and the return on a portfolio of low profitability stocks ($r_{ROE}$).[14]

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[13] Other examples include Tesla, Texas Instruments, 3M and Honeywell in the category of large-cap-growth stocks; and Texas Biotechnology, Novocure and Crocs Inc., in the category of small-cap-growth stocks.

[14] It is noteworthy that the investment and profitability factors in the *q* context, are also present in the *FF*5-factors, are constructed differently than they are by Fama and French although, as HXZ acknowledge, the *q*-factors and the *FF*5 are closely related.

In Table 6, we replicate our main analysis (Table 3) by replacing the *FF5* factors with the *q*5 factors. Following Hou, Mo, Xue and Zhang (2021), we also include the expected growth Factor (*EG*) as an additional risk factor. We obtain monthly data for the five factors from HXZ's website, global-*q*.org. While the alpha estimates are smaller relative to those in Table 3 (0.57% vs 0.62% for *q*5; and 0.58% vs 0.64% for *q*5 + Momentum), they are statistically significant (t-stat = 2.91 and 2.92). Although the *t-stat* for the *low-high* portfolio is slightly below the 3.0 threshold, the economic significance holds. Among the *q*5 factors, however, the market factor *MKT* absorbs most of the loading followed by the *IA* factor which is negative and highly significant. The adjusted R-squares in the current estimations are about the same as in Table 3. This implies that using *q*5 in place of *FF*5 does not improve model explanatory power. In sum, the choice of the control risk factors appears to have no impact on our findings.

## 5. Plausible channels for return premium.

### *5.3. Institutional Ownership*

So far, we have investigated the effect of document complexity on stock returns and show that a self-financed trading strategy of going long on *Easy* portfolio and short on *Complex* portfolio is significantly profitable. We further explore two plausible channels for this return premium: namely the institutional ownership and industry analyses. To do so, we begin by first investigating whether institutional ownership moderates the *complexity* and return relationship. Because firms have a mix of shareholders between individual or retail investors and institutional investors who hold large blocks of shares. Prior research has shown that institutional investors are smart and informed (Chakravarty, 2001; Badrinath, Kale, and Noe, 1995; Sias and Titman, 2006), whereas retail investors are less informed about the companies. Moreover, the presence of institutional investors can affect the overall market reaction to financial disclosures, as they are known to be more sophisticated and less prone to behavioral biases (Gompers and Metrick, 2001). Therefore, a higher proportion of institutional ownership in a firm also conveys a form of certification and greatly increases the firm's disclosure quality. On the other hand, when a firm has higher proportion of retail investors this certification effect is absent, and investors will be more interested in closely understanding the underlying risks of such companies. This argument is also consistent with the previous research, which documents that lower readability attract higher demand for analyst research and lower investor trading (Miller, 2010; Lehavy, Li and Merkley, 2011).

Thus, based on these arguments we posit that firms with higher proportion of retail investor ownership favours lower document complexity (*Easy*) and firms with relatively lower proportion of retail investor ownership favours higher document complexity (*Complex*). Therefore, we test this by first sorting the stocks based on the median ratio of institutional ownership percentage to total shares outstanding (*IO*) in a given year into low and high. Stocks that have above (below) -median *IO* are named as 'high' ('low'), suggesting that such stocks have high (low) institutional ownership (or low retail ownership). Next, within high and low portfolio we further sort stocks based on complexity (XBRL or HTML) into quintile portfolios as before and finally we calculate the low-high portfolio returns by going long on Q1 and short on Q5. If indeed the certification effect holds then the portfolio of stocks with low institutional holdings should have higher low-high alphas relative to the portfolio of stocks with high institutional holdings.

To test the effect of institutional holdings on the relationship between document complexity and returns we re-estimate Table 3 but for low and high portfolio, we see that the low-high monthly premium for low portfolio is 0.56% (t-stat = 4.09) compared to that of 0.23% (t-stat = 2.2). We do not report the regression estimates for brevity but available upon request. More importantly, the results imply that investors prefer lower document complexity in firms with lower institutional holdings relative to those with higher institutional holdings, explaining one plausible channel for higher return premium in less complex disclosures.

### *5.4. Industry portfolios*

We further explore whether inherent accounting complexities in certain industries can explain the channel for the return premium. Because previous research has documented that in addition to idiosyncratic firm-specific complexities, firms in certain industries have underlying common characteristics that may give rise to higher levels of accounting complexity (see, for example, Danos, Eichenseher and Holt. 1989; Stein, Simunic and O'Keefe, 1994; Solomon, Shields and Whittington, 1999; Cahan et al. 2008; SEC 2014; You and Zhang, 2009; Miller, 2010). Mainly accounting complexity arises because of the difficulty in applying or understanding the generally accepted accounting principles (GAAP). For example, services sector has relatively lower accounting difficulty as opposed to other industries such as healthcare or construction where the operating cycles are longer and have complex business models, requiring expertise in interpreting the financial statements. Thus, given the inherent complexities in certain industries we posit that investors will prefer a relatively easier to understand 10-K document in such industries. The underlying intuition is that investors value the document complexity higher for firms in relatively complex industries compared to those in lower complex industry.

Additionally, Lim, Richardson and Smith (2023) document that industries such as Chemicals, Utilities, Banks etc. have higher XBRL tags relative to industries such as retail, manufacturing or energy. Thus, to investigate whether the return premium is higher or lower depending on the industry a firm operates in we examine the low-high premiums for each of the 12 Fama and French broad industry classifications, thereby create 12 industry portfolios each month. Similar to our main test we go long (short) on *Easy* (*Complex*) portfolio within each industry portfolio. From the industry portfolio tests we find that the complexity related low-high return premium is statistically and economically significant among industries such as, healthcare, wholesale and services sector, utilities and construction. For example, the healthcare sector earns a monthly alpha of 1.29% (t-stat = 3.82), mining industry and wholesale services industry earn a monthly alpha of 1.13% (t-stat = 3.17) and 0.55% (t-stat = 2.10) respectively. We also find that among the 12-industry portfolios 10 industries earn an economically significant monthly alphas ranging from 0.16% to 1.65%. We do not report the regression estimates for brevity but available upon request. The results imply that investors prefer lower document complexity and expect higher premium for firms in relatively complex industries compared to others, thus provides an alternative channel for higher return premium in less complex disclosures.

## 6. Addressing 'factor zoo' problem and supplementary tests.

We have, thus far, shown that the XBRL factor is both statistically and economically significant after controlling for widely established factors such as Fama-French and Hou, Xue and Zhang's *q5* factors, along with other bi-variate sorts. However, given the recent evidence of the '*factor zoo*' issue whereby hundreds of factors have been discovered over the past decade, it is reasonable to ask whether XBRL captures a unique risk about stock returns beyond that is documented in the factor zoo.

Harvey, Liu and Zhu (HLZ 2016) present a multiple testing framework to derive a threshold *t-stat* cutoff to classify the truly significant factors. The authors evaluate 316 published factors and provide a guidance as to the appropriate significance level a given factor should be compared against. Specifically, they argue that the usual cutoff level of statistical significance is not appropriate, and any newly constructed factor should clear the threshold *t-stat* of at least 3.0. To do so, they follow the statistics literature in employing three *p-value* adjustment methods: Bonferroni's adjustment, Holm's adjustment and Benjamini, Hochberg and Yekutieli's adjustment.[15] Furthermore, based on the *p-value* adjustments Harvey et al. obtain three benchmark *p-values*, with a corresponding *t-stat* of 3.54, 3.20 and 2.67 for Bonferroni, Holm and Benjamini, Hochberg and Yekutieli's adjustments, respectively. In general, Bonferroni's and Holm's adjustments result in higher rejection rates than the third method (see also Sethuraman et al., 2019).

Hou, Xue and Zhang (HXZ, 2020) replicate the 452 distinct factors that have been documented in the recent finance literature. They use a multiple testing framework to derive a benchmark *t-stat* of at least 2.78 for the return difference between any given factor's top and bottom portfolios. They also suggest employing value-weighted returns in portfolio sorts rather than equal-weighted returns.[16] By that measure, we find that the value-weighted *LOW-HIGH* alpha displays a *t-stat* of 4.10 and an annualized risk-adjusted returns of 7.7%. Therefore, the *LOW-HIGH* returns for the XBRL portfolios comfortably clears all the recommended thresholds by HLZ and HXZ.

[15] Specifically, the Bonferroni's adjustment controls the family-wise error rate (FWER), whereas the Holm's and Benjamini, Hochberg and Yekutieli's adjustment control for false discovery rate (FDR). In general, the FWER is a more stringent adjustment than FDR. Also, the Bonferroni's adjustment is known to be the most stringent test among the three methods (see, for example, Sethuraman, et al., 2019).

[16] Hou, Mo, Xue and Zhang (2019) argue that many recently proposed factors are closely related. They show that their q-factor model largely subsumes the Fama-French five and six-factor models. There is, however, no denying that these five and six factors are fundamental and most, if not all, of the derivative factors are constructed from these basic factors.

More recently, Jensen, Kelly and Pedersen (JKP, 2023) replicate the factors that pass the statistical significance level in HXZ. Specifically, JKP replicate 153 significant factors and argue that the statistical significance of the alphas matters as opposed to that of raw returns. The authors find that about 80% of the 153 factors are replicable even after modifying the factor construction and accounting for multiple testing framework. Furthermore, JKP document that these 153 factors can be grouped across 13 broad themes, because the factors are known to be related under each of the 13 themes identified through a hierarchical clustering approach.[17]

Based on these arguments we formally investigate the following three falsification tests: a) spanning regressions, b) tangency portfolio tests and c) factor-mimicking portfolio test to rule out the possibility of complexity premium being subsumed in other prominent risk factors or whether the premium adds significant value to the investor's portfolio or any spurious relationship significantly affecting the main results. Therefore, in the following sections we first conduct factor spanning tests, followed by calculating the tangency portfolio Sharpe ratios and finally employ the factor-mimicking portfolio tests.

### *6.1. Spanning regressions*

To determine whether the XBRL risk premium is subsumed among the widely used set of factor models, we employ spanning regressions. Because prior studies such as Hou, Mo, Xue and Zhang (2019) employ spanning tests to compare various factor models and show that in factor spanning tests, the *q*-factor and the *q5* factors largely subsume the Fama–French five- and six factor models. Their approach is preceded by other studies that use factor spanning regressions to empirically compare factor models. See for example Fama and French (2015, 2018) and Barillas and Shanken (2017, 2018). Additionally, Barillas and Shanken (2018) through Bayesian analysis propose a six-factor model that includes the market factor (*MKT*), *SMB*, *I/A*, *ROE*, $HML^m$ and *MOM* and show that these six-factors 'dominates' among a set of 10 candidate factors.[18] In a similar spirit as the above mentioned studies we compare the complexity premium with each of the widely established models by estimating various spanning tests in Table 10 to establish that complexity risk premium remain significant and cannot be explained by the previously known models.

Table 10 provides the spanning tests of the *low-high* premium against Fama-French 5-factors (FF-5), *q5* factors, Barillas and Shanken (2018) six-factors (BS-6), Stambaugh and Yuan (2017) factors (SY-4), and finally against the 13 themes across 153 factors by JKP (2022).[19] In Panels A and B of

[17] The 13 factor themes are as follows: Skewness, Profitability, Low-risk, Value, Investment, Seasonality, Debt issuance, Size, Accruals, Low leverage, Profit growth, Momentum, Quality. For additional details on the factor clustering see section 1.2 in JKP (2023).

[18] *SMB* is from Fama and French (2015), *I/A* and *ROE* are from Hou, Xue and Zhang (2015), $HML^m$ is from Asness and Frazzini (2014), *MOM* is from Fama and French (2016).

[19] We use the factor-clusters rather than the individual factors because JKP show that majority of the documented factors can be grouped together across 13 themes (or clusters). Since our purpose is to understand whether

Table 10 we regress the FF-5 and *q5* respectively against the *LOW-HIGH* returns obtained from the XBRL quintile portfolios. We find that the *LOW-HIGH* portfolio earns on average alpha of 0.80% per month (*t-stat* = 3.68) and 1.126% per month (*t-stat* = 2.43) against the FF-5 and *q5* models respectively. In Panel A we also find that *RMW* earns an average alpha of 0.52% per month (*t-stat* = 4.52), whereas *CMA* and *MKT* earn an average alpha of 0.29% per month (*t-stat* = 3.09) and 1.089 respectively, while the other factors do not earn a significant alpha. Similarly, in Panel B we find that the *EG* and *MKT* factors earn significant alphas (0.66%, t-stat = 6.22 and 1.35, t-stat = 6.63) the size (*ME*) earns a weakly significant alpha of 0.32% per month (*t-stat* = 1.77) consistent with Hou et al, (2019) in their Section 3.1.b. Overall, from Panels A and B it is clear that the FF-5 and *q5* models cannot explain the XBRL premium and the *LOW-HIGH* return from XBRL portfolios remain significant and is not subsumed from these two models.

Likewise, in Panels C and D we regress the XBRL premium against Barillas and Shanken (2018) BS-6 and Stambaugh and Yuan (2017) SY-4 models respectively. From Panel C we find that the XBRL premium earns a significant average return of 0.94% per month (*t-stat* = 3.35), with ROE factor earning an average return of 0.48% per month (*t-stat* = 5.06), while the other factors do not earn a statistically significant return. Furthermore, in Panel D we find that XBRL premium earns a significant average return of 0.94% per month (*t-stat* = 3.35). More importantly we find that the XBRL premium survives the SY-4 model and is able to earn a sizeable alpha despite high factor loadings from the *SMBF* factor. In sum, from Panels C and D we find that the XBRL alphas survive the spanning tests against Stambaugh and Yuan (2017) factors and Barillas and Shanken (2018) six-factor model. The significant alphas for the XBRL portfolios suggest that XBRL premium is not subsumed by other factor models and remain significant.

Finally, in Panel E spanning regressions against *MKT* and one of the 13 clusters from JKP. The rationale to include *MKT* factor with each of the themes/cluster is to account for the high correlations across each of the clusters. For example, JKP document a high degree of pair-wise correlation across the 13 different clusters, suggesting that some of the factor themes could be capturing similar risks. Therefore, to ensure that we are capturing the unique information from each factor theme, in our spanning regressions we include one factor cluster at a time along with the *MKT* factor. Panel E reports the regression details for each factor theme from columns (1) through (26). We find that the XBRL portfolio alphas for all models are statistically significant ranging from 0.62% per month (*t-stat* = 2.36) to 1.07% per month (*t-stat* = 3.95). We also find that the factor loadings for *MKT* is significant in 10 of the 13 models, suggesting that the alphas for XBRL premium is significant despite high factor loadings in *MKT*.

complexity premium captures a unique risk that is not embedded in the previously documented factors comparing the factor-clusters provides a concise approach.

Overall, the spanning tests in Table 10 confirm that not only the *low-high* premium is significant but also cannot be explained by a wide array of factors that are documented to explain cross-section of stock returns. Specifically, from the tests in this section we show that the *low-high* premium is unexplained from the standard asset pricing factors. It also cannot be explained by various accounting factors that are documented to be significant in the previous studies.

### *6.2. Tangency portfolio test*

So far, the results from comparing the *complexity low-high* premium with a wide array of factors suggest that recently documented factors do not subsume the risk captured in complexity portfolios. However, JKP (2023) and Hirshleifer, Hou and Teoh (2012) argue that economically important factors are those that have large impact on the investor's overall portfolio. Hence to understand whether the *low-high* premium carry significant weight in a hypothetical investor's portfolio relative to the market and the 13 factor-clusters we estimate *ex-post* weights in a tangency portfolio that invests jointly in each of the cluster along with *MKT* and XBRL portfolio (*low-high*). We constrain all the weights to be non-negative and normalized to sum to one to calculate the Sharpe ratios. If indeed the *low-high* premium is a significant factor, then adding XBRL premium to the portfolio should increase the portfolio Sharpe ratios relative to the portfolio that invests only in *MKT* and one of the 13 clusters.

Table 11 reports the monthly Sharpe ratios and the corresponding weights of the 13 portfolios that invests in the XBRL portfolio, *MKT* and one of the clusters. Specifically in Panel A1 we estimate the ex-post weights and Sharpe ratios for each cluster in a tangency portfolio that invests jointly in each of the cluster along with *MKT*. Next, in Panel A2 we add XBRL to each of the 13 portfolios and estimate the ex-post weights and Sharpe ratios. In Panel A2, we find that the XBRL portfolio carries a highest weight in 7 out of 13 portfolios. More importantly we find that adding XBRL factor in the tangency portfolios substantially increases the portfolio Sharpe ratios ranging from 20% to 63% (except for Seasonality cluster, which increases by 300%). Additionally, in Panel B we also estimate the monthly Sharpe ratios for FF-5 and *q*5 factors and compare those with augmenting XBRL. Here too we find that XBRL receives a significantly high portfolio weight relative to all other factors but for *RMW* and substantially high Sharpe ratio (0.21 versus 0.17) among the FF-5 factors. Among the q5 factors *EG* receives the highest weight of 41%, however the Sharpe ratio increases, although marginally when we add XBRL (0.35 versus 0.33). In Figure 2, we visually compare the increase in the Sharpe ratios by plotting them across the 13 different clusters plus *MKT* factors indicated by dotted lines and compare with the Sharpe ratios after adding XBRL to each corresponding portfolio (indicated by solid line). The results in Table 11 and Figure 3 show that adding XBRL in each of the 13 portfolios that includes the market factor substantially increases the Sharpe ratio and receives a significant weight in the portfolio. The reasons that XBRL dominates the tangency portfolios are driven by higher average returns and lower standard deviation compared to the factor-clusters. Thus, the findings imply that investing in the *low-high* portfolio provides a significant economic value to the investor's portfolio.

### *6.3. Factor mimicking portfolio tests.*

To ensure that our main results are not driven by spurious relationship between XBRL and returns we test for a source of common variation in the returns of our complexity portfolios following Lamont, Polk, and SaáRequejo (2001) and Whited and Wu (2006;2018). Specifically, Lamont et al. (2001) show that financially constrained firms' stock returns move together over time, suggesting that constrained firms are subject to common shocks. Similarly, Whited and Wu (2018) in their Table 6 show that the portfolio returns of firms with financial constraints move together, suggesting that the financial constraints are not idiosyncratic to firms. In our case too intuitively, this test is based on the idea that if XBRL risk is completely idiosyncratic to the firm, then complex firms' returns should not move together, controlling for other sources of common variation among stock returns. If indeed XBRL is a systematic risk factor, then the returns of the XBRL portfolios should move together. Therefore, to test for the co-movement, following the Whited and Wu (2018) approach we employ factor mimicking portfolio (FMP) tests, where we regress the returns of all fifteen double-sorted portfolios on three reference portfolio returns. These reference portfolios consist of a proxy for the market factor (*MKTF*), a proxy for the size factor (*SIZEF*), and the XBRL factor (*XBRLF*). To classify the 15 portfolio combinations (i.e., 5 XBRL portfolios * 3 Size portfolios), we denote portfolios starting with S/M/L as those belonging to the Small/Medium/Large percentile. Similarly, the five *XBRL* quintile portfolios are denoted with $Q_1$, $Q_2$, $Q_3$, $Q_4$ and $Q_5$. We then define the returns for *MKTF* and *SIZEF* as *MKTF* = ($LQ_1$ +$LQ_3$ + $LQ_1$ + $LQ_3$)/4 and *SIZEF* = ($SQ_1$+$SQ_2$+$SQ_3$+ $SQ_4$+$SQ_5$)/5. The *XBRLF*, portfolio is then defined as *XBRLF* = *LOW* - *HIGH*, where *LOW* = ($SQ_1$+ $MQ_1$+ $LQ_1$)/3, and *HIGH* = ($SQ_5$+ $MQ_5$+ $LQ_5$)/3. Therefore, in words, the proxy for the market (*MKTF*) consists of the least-complexity (low XBRL) portfolio medium-size and large-size firms. The proxy for size (*SIZEF*) consists of the least-complexity (low XBRL) small-sized firms. Hence, by construction in all regressions, we exclude the stocks used in constructing the portfolio excess returns (dependent variable) from the construction of the reference portfolios (i.e., *MKTF*, *SIZEF* and *XBRLF*) in order to avoid spurious results.

Table 12 reports the regressions for each of the fifteen portfolios. The regressions show that the returns of *XBRL* portfolios covary with one another. Specifically, for each size category, the coefficient on the *XBRLF* portfolio turns to negative and significant from positive and significant when the portfolio turns to firms consisting of least complex to most complex. For example, the coefficients on *XBRLF* for the least complex portfolios (i.e., $Q_1$) are positive and significant (coefficient = 0.42, 0.13, 0.36; t-statistic = 9.07,1.54 and 2.51 respectively) across the small, medium and large portfolios. In contrast, the coefficients on *XBRLF* for the most complex portfolios (i.e., $Q_5$) are negative and significant (coefficient = -0.51, -0.74, -0.85; t-statistic = -8.89, -9.20 and -13.48 respectively). We also find that this pattern is consistent across the three Size portfolios (i.e., S, M, L). These results show that the returns of firms with fewer XBRL covary positively with the returns of other firms that contain fewer XBRL characters, even if we condition on proxies for the market and size. Thus, the results in Table 12 confirms that the *low-high* premium through XBRL is not idiosyncratic to the firm, rather a broader trading strategy that can be used to explain the variation in cross-section of stock returns.

### *6.4. Stock-level regressions.*

Thus far, we have aggregated individual stocks in portfolios in an effort to examine whether the *low-high* XBRL portfolio returns earn significant premium. The rationale for creating a portfolio of risky assets goes back to Blume (1970) who reasoned that examining the determinants of stock returns of stocks individually would give rise to an errors-in-variables problem with the estimated betas. And, if the errors in the estimated betas are imperfectly correlated across stocks, these errors would cancel each other out when combined into portfolios and the factor risk premia would be accurately estimated. The portfolio approach was then adopted by Black, Jensen and Scholes (1972), Fama and MacBeth (1973), among others. More recently, however, Petersen (2009) argues that when considering a general panel data set up with both firm and time effects, one can address the two sources of correlation by parametrically estimating one of the dimensions through the inclusion of dummy variables. Since panel data sets usually have more firms than years, an efficient approach is to include dummy variables for each time period (thereby absorbing the time effect) and then cluster by firm (see, also, Faulkender and Petersen, 2006). If the time effect is fixed, the time dummies would completely remove the correlation between observations over the same time period. What is then left in the data are only the firm effects where the OLS and Fama-MacBeth standard errors are biased, while the standard errors clustered by firm are unbiased. Therefore, by using individual stocks and employing the Petersen approach, we should be able to efficiently test whether certain factors are priced.

Hence, we estimate our model on an individual stock basis first, following the classical Fama-McBeth (1973) approach and then using panel fixed effect regressions with clustered standard errors as suggested by Petersen (2009). In these stock level regressions, we use *XBRL*, defined as the natural logarithm of XBRL or HTML characters. (identified as *Log* XBRL) in each 10-K, as our measure for document complexity. Table 9 provides the results for the Fama-MacBeth regressions in Columns 1 and 2 while Columns 3 and 4 provide results of the fixed effects with clustered standard errors (Petersen ,2009) approach. The dependent variable is the cumulative abnormal annual returns over the following two quarters from the 10-K announcement month, adjusted for the risk-free rate. This is computed on a similar spirit as Buehlmaier and Whited (2018) to avoid any look-ahead bias in our estimations. Our independent variables follow those used by Jegadeesh and Wu (2013) in their stock level regressions and are as follows: the log of book-to-market ratio (*Log BM*); *Volatility*, defined as the standard deviation of the firm-specific component of returns estimated using up to 12 months of data as of the end of the month before filing date; and *Turnover* defined as the natural logarithm of the number of shares traded during the period from -252 days to -6 days relative to the 10-K filing date divided by the number of shares outstanding on the filing date; *Log SIZE* defined as the natural logarithm of the market capitalization of equity at the end of the month before the 10-K filing date. Finally, *Accruals* is computed as in Sloan (1996).[20]

With the Fama-MacBeth regressions, we estimate the two-step approach each month and report the average coefficients based on the 335 monthly regressions. The standard errors are adjusted for Newey-West with 1-year lag. Column 1 includes *Log XBRL* as the explanatory variable, whereas Column 2 augments with other control variables. From Columns 1 and 2 we find that *Log XBRL* is negative and statistically significant, consistent with our baseline results. The negative relationship with cumulative returns suggests that investors react negatively to stocks with high linguistic XBRL. *SIZE* and *BM* are both negative and statistically significant at the 0.01 level. In columns 3 and 4 too we find that *Log XBRL* has a negative and significant correlation with cumulative returns suggesting that stocks with high linguistic XBRL have lower returns. Overall, we see that our XBRL proxy contains novel information not subsumed by any of the other prominent risk measures even at the individual stock level.

## 7. Conclusion

We construct a novel risk factor based on the document complexity of firms' annual 10-K filings and show that a trading strategy of buying easy stocks and selling complex stocks generates abnormal returns that are both statistically and economically significant. Specifically, a self-financing low-high portfolio trading strategy, by going long on least complex (or fewer XBRL) stocks and by shorting most complex (or more XBRL) stocks, yields an average annual return of approximately 9.1 percent over our 28-year sample. Upon partitioning the data on firm size and book-to-market ratio, we show that the impact of XBRL premium is the strongest among the relatively smaller-sized firms and growth-oriented firms. We also consider other partitions of the data, like excluding the crises periods such as dot-com bubble and global financial crisis. Additionally, we identify a plausible channel: institutional ownership, which can explain the return premium. We also estimate individual stock-level regressions and to ensure that the return premium is not driven by any spurious relationship or is subsumed by other prominent

[20] Specifically, *Accruals* is computed as a difference in one-year change in current assets minus change in cash/cash equivalents and change in current liabilities excluding long-term debt in current liabilities minus taxes payables minus depreciation, whole divided by average total assets (measured as the average of the beginning and end of year, book value of total assets). Formally:

$$\text{Accruals} = \frac{(\Delta\text{CA} - \Delta\text{Cash}) - (\Delta\text{CL} - \Delta\text{D} - \Delta\text{TP}) - Dep}{\text{Average Total Assets}}$$

ΔCA = one-year change in current assets (Compustat item 4), ΔCash = one-year change in cash/cash equivalents (Compustat item 1), ΔCL = one-year change in current liabilities (Compustat item 5), ΔD = one-year change in debt included in current liabilities (Compustat item 34), ΔTP = one-year change in income taxes payable (Compustat item 71), and Dep = depreciation and amortization expense (Compustat item 14). Average Total Assets = average of the beginning and end of year, book value of total assets (Compustat data item 6).

factors we conduct the spanning test, tangency portfolio test and factor mimicking portfolio tests. Overall, our research suggests that any contemporary or future work on asset pricing should reasonably include a risk measure capturing the underlying document complexity of any relevant written communication directly or tangentially associated with the research question being investigated.

While we take a small, but significant, step in quantifying the impact of a XBRL-based risk factor and demonstrating its robustness, we leave it to future research to thoroughly investigate the breadth and depth of the impact of similar qualitative risk measures estimated through cutting edge AI tools that are now widely used in marketing analysis as well as in election vote targeting models. It is clear that the qualitative risk related genie is out of the bottle and the asset pricing research landscape will look very different in the coming years.

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**Figure 1: Low-high complexity portfolio returns versus S&P value-weighted monthly returns.**

This graph plots the low-high monthly returns (solid-line) constructed using the complexity portfolios against S&P value-weighted (VW) monthly returns (dotted-line).

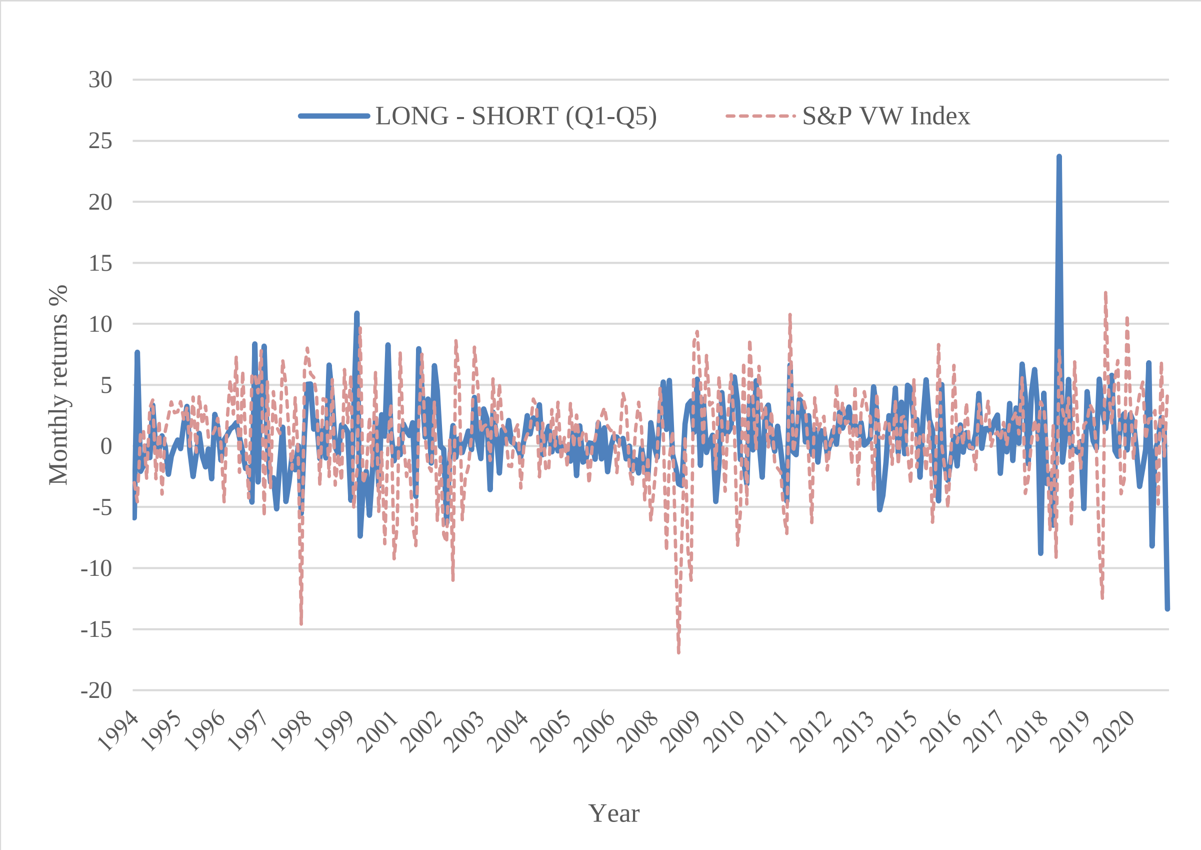

**Table 1: Summary Statistics**

This table presents the summary statistics of firm characteristics used in our analyses. The sample period is from 1994 through 2021. The table reports the mean, median, minimum, maximum and standard deviation (SD) of the monthly market capitalization (*SIZE*) and the book-to-market ratio (*BM*). Operating Profitability (OP) is defined as revenues minus cost of goods sold, minus selling, general, and administrative expenses, minus interest expense all divided by book equity through the Compustat data items [SALE - (COGS - XSGA - XINT)] divided by BE [BE = sum (AT, -LT, -PSTKL, TXDITC, DCVT]. Investments (*Inv*) is computed as the change in total assets from the fiscal year ending in year *t-2* to the fiscal year ending in *t-1*, divided by *t-2* total assets, computed annually at the end of each June. We operationalized *Inv* through the Compustat data item – 6 (item name – AT). All the values are winsorized based on 1st and 99th percentile.

| | **Mean** | **Median** | **Min** | **Max** | **SD** |
|---|---|---|---|---|---|
| *Size (Mn)* | 3,843.91 | 518.68 | 44.70 | 511887.13 | 17564.514 |
| *BM (Mn)* | 0.63 | 0.471 | 0.032 | 2.21 | 12.887 |
| *OP* | 0.253 | 0.272 | -1.85 | 2.80 | 21.093 |
| *Inv* | -0.095 | -0.079 | -8.84 | 0.65 | 0.259 |
| Monthly return volatility | 0.136 | 0.116 | 0.009 | 3.927 | 0.089 |
| XBRL Characters | 3,375,786 | 3,162,703 | 0.000 | 10,079,739 | 1,648,843 |
| HTML Characters | 686,763 | 336,802 | 50.00 | 27,345,590 | 1,133,822.2 |
| Total words/10-K | 43,049 | 35,746 | 6,992 | 606,603 | 31,174 |
| Net file size (MB) | 3.3 | 0.28 | 0.003 | 44.89 | 0.23 |

**Table 2: Univariate statistics of *complexity*-based portfolios**

This table presents the univariate portfolio returns when sorted on *complexity* into quintiles, identified as *Easy* (Q1 of *XBRL*) and *Complex* (Q5 of *XBRL*). Panel A reports the equal-weighted and value-weighted portfolio gross-monthly returns. Panel B reports the equal-weighted and value-weighted DGTW adjusted portfolio monthly returns. The corresponding t-statistics for each quintile is reported in the adjacent columns, that tests for the null that the difference is significantly different from zero. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

**Panel A: portfolio returns based on linguistic XBRL**.

| | Value - weighted | | | | Equal - Weighted | | | |
|---|---|---|---|---|---|---|---|---|
| XBRL portfolios | Gross Returns % | t-stat | Net Returns % | t-stat | Gross Returns % | t-stat | Net Returns % | t-stat |
| Q1 (*Easy*) | 1.98*** | 6.50 | 1.39*** | 8.21 | 1.56*** | 4.50 | 0.78*** | 3.58 |
| Q2 | 2.00*** | 6.90 | 1.40*** | 8.71 | 1.47*** | 4.13 | 0.69*** | 3.18 |
| Q3 | 1.88*** | 6.09 | 1.28*** | 6.95 | 1.43*** | 3.97 | 0.65*** | 3.00 |
| Q4 | 1.59*** | 6.31 | 0.99*** | 8.90 | 1.25*** | 3.53 | 0.46** | 2.30 |
| Q5 (*Complex*) | 1.35*** | 5.58 | 0.75*** | 10.09 | 1.18*** | 3.43 | 0.41** | 2.23 |
| Long - Short (Q1-Q5) | 0.63*** | 3.63 | 0.63*** | 3.63 | 0.37*** | 2.72 | 0.37*** | 2.72 |

**Panel B: DGTW benchmark adjusted returns for XBRL portfolios.**

| XBRL portfolios | VW - Returns % | t-stat | EW Returns % | t-stat |
|---|---|---|---|---|
| Q1 (*Easy*) | 1.23*** | 9.41 | 0.84*** | 8.04 |
| Q2 | 0.97*** | 7.06 | 0.70*** | 7.92 |
| Q3 | 1.06*** | 7.42 | 0.60*** | 7.04 |
| Q4 | 0.72*** | 7.96 | 0.42*** | 5.62 |
| Q5 (*Complex*) | 0.49*** | 6.09 | 0.37*** | 4.54 |
| Long - Short (Q1-Q5) | 0.73*** | 5.23 | 0.47*** | 4.00 |

**Table 3: Portfolios sorted on *Complexity*.**

This table presents regressions of the low-high value-weighted portfolios that are sorted on *Complexity* into quintiles and deciles, identified as *Easy* (Q1 of *XBRL*) and *Complex* (Q5 or D10 of *XBRL*). Panel A reports the results for baseline models and Panel B reports the results after excluding the dot-com bubble period (June 1999 through July 2001) and global financial crisis (December 2007 through June 2009). The '*Alpha*' represents the monthly risk-adjusted returns (in %) for the low-high (*Easy* – *Complex*) *Complexity* portfolios. "# Stocks" shows the average number of stocks in the portfolio. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The corresponding t-statistics (indicated as *t-stat*) are presented in the adjacent row for each parameter.

**Panel A: Baseline models**

| Parameter | Quintile - Sort | | Decile - Sort | |
|---|---|---|---|---|
| Long – Short portfolio (*Easy* – *Complex*) | | | | |
| | (1) | (2) | (3) | (4) |
| | FF5 | FF5 + Momentum | FF5 | FF5 + Momentum |
| ***Alpha (monthly %)*** | **0.617*** ** | **0.643*** ** | **0.802*** ** | **0.851*** ** |
| ***t-stat*** | **4.10** | **4.21** | **3.68** | **3.47** |
| *SMB* | 0.397*** | 0.408*** | 0.650*** | 0.672*** |
| *t-stat* | 6.13 | 6.21 | 6.15 | 5.76 |
| *HML* | -0.093 | -0.112 | -0.161 | -0.194* |
| *t-stat* | -1.38 | -1.61 | -1.64 | -1.97 |
| *RMW* | -0.060 | -0.055 | 0.089 | 0.099 |
| *t-stat* | -0.80 | -0.70 | 0.79 | 0.82 |
| *CMA* | -0.117 | -0.105 | -0.001 | 0.022 |
| *t-stat* | -1.16 | -1.01 | -0.01 | 0.17 |
| *MKT* | 0.026 | 0.009 | 0.127 | 0.097 |
| *t-stat* | 0.55 | 0.18 | 1.41 | 1.26 |
| *WML* | | -0.056 | | -0.102 |
| *t-stat* | | -0.96 | | -0.98 |
| *Adjusted* $R^2$ | 0.20 | 0.20 | 0.13 | 0.14 |
| *# Obs.* | 335 | 335 | 335 | 335 |
| *Avg.# Stocks* | 343 | 343 | 172 | 172 |

**Panel B: Re-estimating Baseline models <u>after</u> removing the dot-com bubble period (June 1999 through July 2001) and global financial crisis (December 2007 through June 2009)**

| Parameter | Quintile - Sort | | Decile - Sort | |
|---|---|---|---|---|
| | Long – Short portfolio (*Easy* – *Complex*) | | | |
| | (1) | (2) | (3) | (4) |
| ***Alpha (monthly %)*** | **0.730***** | **0.750***** | **0.900***** | **1.001***** |
| ***t-stat*** | **5.00** | **4.77** | **3.83** | **3.43** |
| *SMB* | 0.451*** | 0.453*** | 0.818*** | 0.826*** |
| *t-stat* | 6.37 | 6.33 | 7.16 | 7.00 |
| *HML* | -0.194*** | -0.199*** | -0.310*** | -0.337*** |
| *t-stat* | -2.79 | -2.80 | -2.67 | -2.83 |
| *RMW* | -0.254*** | -0.238** | -0.014 | 0.069 |
| *t-stat* | -2.78 | -2.40 | -0.11 | 0.42 |
| *CMA* | -0.219* | -0.225* | -0.029 | -0.057 |
| *t-stat* | -1.94 | -1.96 | -0.18 | -0.32 |
| *MKT* | -0.001 | -0.011 | 0.122 | 0.068 |
| *t-stat* | -0.01 | -0.24 | 1.18 | 0.88 |
| *WML* | | -0.048 | | -0.24 |
| *t-stat* | | -0.59 | | -1.25 |
| *Adjusted* $R^2$ | 0.16 | 0.17 | 0.25 | 0.27 |
| *# Obs.* | 290 | 290 | 290 | 290 |

**Table 4: Excess returns of double sorts on *SIZE* and *Complexity* and *BM and Complexity***

This table presents monthly excess returns for portfolios that are double sorted on *SIZE* and *Complexity* (in Panel A) and *BM* and *Complex* (in Panel B). In Panel A we first sort on *SIZE* into *Small*, *Medium* and *Large* based on NYSE breakpoints and within each *SIZE* classification we further sort into *XBRL* quintiles, identified as *Easy* (Q1 of *XBRL*) and *Complex* (Q5 of *XBRL*). Similarly, in Panel B, we first sort on *BM* into *High*, *Mid* and *Low* based on the NYSE breakpoints. Within each *BM* classification we further sort into *Complexity* quintiles. The corresponding t-statistics for each quintile are reported in the adjacent columns, that tests for the null that the difference is significantly different from zero. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

**Panel A: Monthly excess returns (%) of double sorts on *SIZE* and *Complexity***

| | Q1(*Easy*) | Q5(*Complex*) | Long - Short (Q1-Q5) |
|---|---|---|---|
| *Small* | 1.8*** | 1.1** | 0.77*** |
| t-stat | 4.74 | 2.38 | 4.52 |
| *Medium* | 2.2*** | 1.6*** | 0.55*** |
| t-stat | 6.19 | 4.54 | 3.36 |
| *Large* | 2.2*** | 1.5*** | 0.69*** |
| t-stat | 7.01 | 6.37 | 3.19 |

**Panel B: Monthly excess returns (%) of double sorts on *BM* and *Complexity***

| | Q1(*Easy*) | Q5(*Complex*) | Long - Short (Q1-Q5) |
|---|---|---|---|
| *Low* | 2.645*** | 2.065*** | 0.694*** |
| t-stat | 6.140 | 5.730 | 3.66 |
| *Mid* | 1.562*** | 1.333*** | 0.236* |
| t-stat | 4.770 | 3.990 | 1.84 |
| *High* | 0.676** | 0.656 | 0.020 |
| t-stat | 2.060 | 1.660 | 0.12 |

**Table 5: Risk-adjusted returns: *Complexity* versus *SIZE* and *BM***

This table presents monthly risk adjusted returns for portfolios that are double sorted on *SIZE* and *Complexity* (in Panel A) and *BM* and *Complexity* (in Panel B). In Panel A we first sort on *SIZE* into *Small*, *Medium* and *Large* based on NYSE breakpoints and within each *SIZE* classification we further sort into *Complexity* quintiles, identified as *Easy* (Q1 of *XBRL*) and *Complex* (Q5 of *XBRL*). Similarly, in Panel B, we first sort on *BM* into *High*, *Mid* and *Low* based on the NYSE breakpoints. Within each *BM* classification we further sort into *Complexity* quintiles. The '*Alpha*' represents the monthly risk-adjusted returns (in %) for the *low-high* (*Easy* – *Complex*) portfolios for each *SIZE* or *BM* portfolio. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The corresponding t-statistics (indicated as *t-stat*) are presented in the adjacent row for each parameter.

**Panel A: Double sorts on *SIZE* and *Complexity***

| Long – Short portfolio (*Easy* – *Complex*) | | | | | | |
|---|---|---|---|---|---|---|
| | FF5 factors | | | FF5 + Momentum | | |
| | Small | Medium | Large | Small | Medium | Large |
| Parameter | (1) | (2) | (3) | (4) | (5) | (6) |
| ***Alpha (monthly %)*** | **1.020*** ** | **0.824*** ** | **0.685*** ** | **0.939*** ** | **0.759*** ** | **0.714*** ** |
| ***t-stat*** | **6.16** | **5.29** | **3.31** | **5.79** | **4.99** | **3.39** |
| *SMB* | 0.015 | 0.091 | 0.260*** | -0.031 | 0.056 | 0.273*** |
| *t-stat* | 0.26 | 1.57 | 3.20 | -0.59 | 0.92 | 3.26 |
| *HML* | -0.244*** | -0.252*** | -0.151* | -0.181** | -0.204*** | -0.171** |
| *t-stat* | -3.36 | -3.82 | -1.87 | -2.52 | -3.30 | -2.08 |
| *RMW* | -0.071 | -0.287*** | 0.002 | -0.090 | -0.302*** | 0.008 |
| *t-stat* | -0.72 | -3.28 | 0.02 | -1.13 | -3.84 | 0.08 |
| *CMA* | -0.171 | -0.125 | -0.150 | -0.220* | -0.162* | -0.137 |
| *t-stat* | -1.24 | -1.32 | -1.23 | -1.69 | -1.87 | -1.12 |
| *MKT* | -0.234*** | -0.191*** | 0.015 | -0.179*** | -0.148*** | -0.004 |
| *t-stat* | -5.86 | -4.65 | 0.24 | -4.20 | -3.47 | -0.06 |
| *WML* | | | | 0.18*** | 0.14*** | -0.061 |
| *t-stat* | | | | 2.82 | 3.26 | -0.81 |
| Adjusted $R^2$ | 0.18 | 0.30 | 0.06 | 0.24 | 0.33 | 0.06 |
| # Obs. | 335 | 335 | 335 | 335 | 335 | 335 |
| Avg.# Stocks | 183 | 99 | 61 | 183 | 99 | 61 |

**Panel B: Double sorts on BM and *Complexity***

| Long – Short portfolio (*Easy* – *Complex*) | | | | | | |
|---|---|---|---|---|---|---|
| | FF5 factors | | | FF5 + Momentum | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Parameter | Low-BM | Mid-BM | High-BM | Low-BM | Mid-BM | High-BM |
| ***Alpha (monthly %)*** | **0.793*** ** | **0.382*** ** | **0.389** ** | **0.776*** ** | **0.334*** ** | **0.300* ** |
| ***t-stat*** | **5.32** | **3.27** | **2.64** | **4.98** | **2.79** | **2.10** |
| *SMB* | 0.365*** | 0.229*** | 0.029 | 0.357*** | 0.205*** | -0.011 |
| *t-stat* | 5.69 | 5.28 | 0.48 | 5.26 | 5.09 | -0.21 |
| *HML* | -0.179*** | -0.156*** | -0.173** | -0.165** | -0.115** | -0.111 |
| *t-stat* | -2.62 | -2.85 | -2.39 | -2.39 | -2.04 | -1.51 |
| *RMW* | -0.204** | -0.090 | -0.134 | -0.208** | -0.102* | -0.153* |
| *t-stat* | -2.46 | -1.35 | -1.34 | -2.45 | -1.78 | -1.79 |
| *CMA* | -0.085 | -0.071 | -0.208 | -0.095 | -0.101 | -0.251** |
| *t-stat* | -0.77 | -0.75 | -1.63 | -0.87 | -1.14 | -2.06 |
| *MKT* | -0.087* | -0.178*** | -0.349*** | -0.075 | -0.146*** | -0.293*** |
| *t-stat* | -1.84 | -5.40 | -7.38 | -1.50 | -3.95 | -6.15 |
| *WML* | | | | 0.038 | 0.11** | 0.18*** |
| *t-stat* | | | | 0.61 | 2.28 | 3.28 |
| Adjusted $R^2$ | 0.24 | 0.22 | 0.26 | 0.24 | 0.24 | 0.31 |
| # Obs. | 322 | 322 | 322 | 322 | 322 | 322 |
| Avg.# Stocks | 122 | 126 | 94 | 122 | 126 | 94 |

**Table 6: Re-estimating Table 3 with *q*5 factors in place of *FF5* factors**

This table re-estimates regressions of the low-high value-weighted portfolios that are sorted on *XBRL* into quintiles and deciles, identified as *Easy* (Q1 of *XBRL*) and *Complex* (Q5 or D10 of *XBRL*) from Table 3 but replaces *FF5* factors with *q5*. Panel A reports the results for baseline models. The '*Alpha*' represents the monthly risk-adjusted returns (in %) for the *Easy* – *Complex* portfolios. "# Stocks" shows the average number of stocks in the portfolio. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The corresponding t-statistics (indicated as *t-stat*) are presented in the adjacent row for each parameter.

| Parameter | Quintile - Sort | | Decile - Sort | |
|---|---|---|---|---|
| | Long – Short portfolio (*Easy* – *Complex*) | | | |
| | (1) | (2) | (3) | (4) |
| | *q5* | *q5* + Momentum | *q5* | *q5* + Momentum |
| ***Alpha (monthly %)*** | 0.570*** | 0.576*** | 1.126** | 1.134** |
| ***t-stat*** | 2.91 | 2.92 | 2.43 | 2.42 |
| *MKT* | 0.010 | -0.001 | 0.026 | 0.012 |
| *t-stat* | 0.23 | -0.01 | 0.47 | 0.22 |
| *ME* | 0.395*** | 0.418*** | 0.497*** | 0.526*** |
| *t-stat* | 6.26 | 6.59 | 5.07 | 5.47 |
| *IA* | -0.215** | -0.226** | -0.136 | -0.150 |
| *t-stat* | -2.26 | -2.34 | -1.25 | -1.33 |
| *ROE* | -0.155* | -0.130 | -0.017 | 0.014 |
| *t-stat* | -1.84 | -1.39 | -0.13 | 0.10 |
| *EG* | 0.116 | 0.127 | -0.330 | -0.317 |
| *t-stat* | 0.79 | 0.88 | -0.86 | -0.83 |
| *WML* | | -0.053 | | -0.067 |
| *t-stat* | | -0.95 | | -0.80 |
| *Adjusted $R^2$* | 0.20 | 0.21 | 0.14 | 0.13 |
| *# Obs.* | 335 | 335 | 335 | 335 |
| *Avg.# Stocks* | | | | |

**Table 7: Stock-level regressions of cumulative returns on individual firm characteristics.** This table shows the results for Fama-MacBeth regressions (in Columns 1 & 2) and fixed effects panel regressions with clustered standard errors of Petersen (2009) (in Columns 3 & 4). The dependent variable is the cumulative abnormal annual returns over the following 2 quarters from the 10-K announcement month, adjusted for the risk-free rate. Independent variables are natural logarithm of XBRL (*Log XBRL*), log of book-to-market ratio (Log *BM*), where *BM* is defined as the ratio of the book value of equity as of the fiscal year-end in the 10-K, *Volatility* is the standard deviation of the firm-specific component of returns estimated using up to 12 months of data as of the end of the month before the filing date, and *Turnover* is the natural logarithm of the number of shares traded during the period from six to 252 trading days before the filing date divided by the number of shares outstanding on the filing date, log of *SIZE* (Log *SIZE*) is the natural logarithm of the market capitalization of equity at the end of the month before the 10-K filing date. *Accruals* is computed as in Sloan (1996). In Panel A, we estimate the two-step Fama-MacBeth regressions each month and report the average coefficients based on the 335 monthly regressions. The standard errors are adjusted for Newey-West with 1-year lag. In Panel B, we report the firm and year fixed effects panel regressions, and the standard errors are clustered for firms and year as in Petersen (2009). Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The corresponding t-statistics (indicated as t-stat) are presented in the adjacent columns.

| **Dependent: Cumulative abnormal returns** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | **Fama-Macbeth** | | | | **Fixed effects Panel regressions** | | | |
| | **1** | | **2** | | **3** | | **4** | |
| **Parameter** | **Estimate** | **t-stat** | **Estimate** | **t-stat** | **Estimate** | **t-stat** | **Estimate** | **t-stat** |
| *Intercept* | 2.5*** | 4.71 | 1.96*** | 4.26 | 0.663 | 0.05 | -0.658 | -0.35 |
| *Log XBRL* | -17.26*** | -4.71 | -23.74*** | -4.63 | -5.3*** | -13.29 | -5.604*** | -14.07 |
| *Log SIZE* | | | 14.52*** | 4.46 | | | 4.927*** | 5.44 |
| *Log BM* | | | 21.81*** | 4.9 | | | 26.823*** | 7.77 |
| *Log Turnover* | | | -9.35** | -2.21 | | | 12.553*** | 11.22 |
| *Volatility* | | | 5.80*** | 3.72 | | | 3.57*** | 45.67 |
| *Accruals* | | | 0.00** | -2.96 | | | -0.001 | -1.00 |
| *# Obs.* | 464,560 | | 464,560 | | 464,560 | | 464,560 | |

**Table 8: Spanning regressions.**

This table presents spanning regressions of the low-high returns (*Easy – Complex*) against Fama and French (*FF-5*,2015), Hou, Xue and Zhang (2015) – *q5*, Stambaugh and Yuan (2017) - *SY-4*, Barillas and Shanken (2018) – *BS-6* factors and Jensen, Kelly and Pedersen (2022) - JKP 13 factor clusters in Panels A - E. The '*Alpha*' represents the intercept for each spanning regression. The monthly factors are obtained from Kenneth French, q group, Robert Stambaugh, AQR Capital and Brian Kelly respectively. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Corresponding t-statistics (indicated as t-stat) are presented in the adjacent row for each parameter.

Panel A: Spanning regressions with *FF-5* factors.

| | *low-high* | *SMB* | *HML* | *RMW* | *CMA* | *MKT* |
|---|---|---|---|---|---|---|
| ***Alpha (monthly %)*** | **0.802*** ** | 0.122 | -0.379** | **0.523*** ** | **0.296*** ** | **1.089*** ** |
| ***t-stat*** | **3.68** | 0.80 | -2.42 | **4.52** | **3.09** | **5.28** |
| *SMB* | 0.650*** | | 0.145** | -0.365*** | 0.028 | 0.069 |
| *t-stat* | 6.15 | | 2.09 | -4.94 | 0.68 | 0.63 |
| *HML* | -0.161 | 0.178** | | 0.364*** | 0.392*** | 0.452*** |
| *t-stat* | -1.64 | 2.38 | | 4.65 | 10.68 | 3.91 |
| *RMW* | 0.089 | -0.556*** | 0.452*** | | | -0.051 |
| *t-stat* | 0.79 | -4.85 | 5.16 | | -0.76 | -4.56 |
| *CMA* | -0.001 | 0.077 | 0.890*** | -0.094 | | -0.906*** |
| *t-stat* | -0.01 | 0.66 | 11.98 | -0.76 | | -5.28 |
| *MKT* | 0.127 | 0.021 | 0.166*** | -0.170*** | -0.147*** | |
| *t-stat* | 1.41 | 0.46 | 3.44 | -4.35 | -5.38 | |
| *low-high* | | 0.158** | -0.032 | 0.014 | -0.000 | 0.046 |
| *t-stat* | | 2.33 | -1.31 | 0.92 | -0.01 | 0.57 |
| *Adjusted $R^2$* | 0.14 | 0.33 | 0.48 | 0.44 | 0.45 | 0.25 |
| *# Obs.* | 335 | 335 | 335 | 335 | 335 | 335 |

Panel B: Spanning regressions with *q5* factors.

| | *low-high* | *ME* | *IA* | *ROE* | *EG* | *MKT* |
|---|---|---|---|---|---|---|
| ***Alpha (monthly %)*** | **1.126** ** | **0.319* ** | **0.319** ** | 0.114 | **0.664*** ** | **1.356*** ** |
| ***t-stat*** | **2.43** | **1.77** | **2.40** | 0.80 | **6.22** | **6.63** |
| *ME* | 0.497*** | | 0.028 | -0.120* | -0.115*** | 0.015 |
| *t-stat* | 5.07 | | 0.44 | -1.96 | -2.76 | 0.14 |
| *IA* | -0.136 | 0.054 | | 0.084 | -0.053 | -0.443*** |
| *t-stat* | -1.25 | 0.46 | | 0.92 | -0.80 | -3.94 |
| *ROE* | -0.017 | -0.197* | 0.073 | | 0.368*** | -0.347*** |
| *t-stat* | -0.13 | -1.65 | 0.86 | | 6.78 | -3.03 |
| *EG* | -0.330 | -0.312*** | -0.077 | 0.608*** | | -0.577*** |
| *t-stat* | -0.86 | -3.27 | -0.82 | 7.40 | | -4.06 |
| *MKT* | 0.026 | 0.008 | -0.136*** | -0.122*** | -0.123*** | |
| *t-stat* | 0.47 | 0.14 | -3.89 | -2.61 | -4.42 | |
| *low-high* | | 0.143 | -0.021 | -0.003 | -0.035 | 0.013 |
| *t-stat* | | 1.63 | -1.19 | -0.12 | -1.37 | 0.48 |
| *Adjusted $R^2$* | 0.14 | 0.24 | 0.08 | 0.45 | 0.48 | 0.31 |
| *# Obs.* | 335 | 335 | 335 | 335 | 335 | 335 |

Panel C: Spanning regressions with *BS-6* factors.

| | *XBRL* | *SMB* | *HML$^m$* | *IA* | *ROE* | *MOM* |
|---|---|---|---|---|---|---|
| ***Alpha (monthly %)*** | **0.936***** | **0.043** | 0.195 | 0.093 | **0.482***** | 0.003* |
| ***t-stat*** | **3.35** | **0.29** | 1.20 | 0.92 | **3.90** | 1.81 |
| *SMB* | 0.651*** | | 0.110 | -0.014 | -0.386*** | 0.003*** |
| *t-stat* | 6.88 | | 1.61 | -0.35 | -5.85 | 3.35 |
| *HML$^m$* | -0.205* | 0.115* | | 0.407*** | -0.150** | -0.007*** |
| *t-stat* | -1.78 | 1.69 | | 11.86 | -2.49 | -7.09 |
| *IA* | 0.085 | -0.034 | 0.974*** | | 0.241*** | 0.005*** |
| *t-stat* | 0.60 | -0.35 | 9.10 | | 2.62 | 3.18 |
| *ROE* | -0.033 | -0.523*** | -0.194** | 0.131** | | 0.002** |
| *t-stat* | -0.30 | -5.59 | -2.50 | 2.54 | | 2.36 |
| *MOM* | -0.19* | 0.31*** | -0.58*** | 0.19*** | 0.16** | |
| *t-stat* | -1.93 | 3.85 | -8.77 | 3.82 | 2.54 | |
| *MKT* | 0.086 | 0.040 | 0.030 | -0.096*** | -0.144*** | -0.001** |
| *t-stat* | 1.24 | 0.94 | 0.60 | -3.20 | -3.99 | -2.10 |
| *low-high* | | 0.149** | -0.045 | 0.008 | -0.006 | -0.000** |
| *t-stat* | | 2.18 | -1.41 | 0.56 | -0.30 | -2.21 |
| *Adjusted $R^2$* | 0.14 | 0.37 | 0.63 | 0.45 | 0.47 | 0.55 |
| *# Obs.* | 335 | 335 | 335 | 335 | 335 | 335 |

Panel D: Spanning regressions with *SY-4* factors.

| | *low-high* | *SMB* | *MGMT* | *PERF* | *MKT* |
|---|---|---|---|---|---|
| ***Alpha (monthly %)*** | 0.923*** | 0.238 | 0.008*** | 0.008*** | 1.237*** |
| ***t-stat*** | 3.00 | 1.38 | 5.00 | 5.54 | 6.17 |
| *SMBF* | 0.584*** | | -0.003*** | -0.003*** | -0.058 |
| *t-stat* | 7.67 | | -3.06 | -3.71 | -0.59 |
| *MGMT* | -5.422 | -26.170** | | -0.111 | -47.495*** |
| *t-stat* | -0.57 | -2.27 | | -1.06 | -6.68 |
| *PERF* | -7.725 | -27.110*** | -0.121 | | -57.722*** |
| *t-stat* | -0.64 | -3.66 | -1.20 | | -6.91 |
| *MKT* | 0.087 | -0.031 | -0.003*** | -0.003*** | |
| *t-stat* | 1.18 | -0.57 | -5.28 | -6.73 | |
| *low-high* | | 0.155** | -0.000 | -0.000 | 0.043 |
| *t-stat* | | 2.00 | -0.62 | -0.76 | 1.52 |
| *Adjusted $R^2$* | 0.14 | 0.26 | 0.22 | 0.27 | 0.31 |
| *# Obs.* | 335 | 335 | 335 | 335 | 335 |

Panel E: Spanning regressions with Jensen, Kelly and Pedersen (2022) factor-clusters.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *low-high* | Size | *low-high* | Low Leverage | *low-high* | Low risk | *low-high* | Seasonality | *low-high* | Skewness | *low-high* | Momentum | *low-high* | Profitability |
| *Alpha (monthly %)* | **0.840*** ** | -0.001 | **0.883*** ** | -0.003 | **1.064*** ** | 0.008*** | **0.773*** ** | -0.041*** | **0.855*** ** | 0.001 | **0.819*** ** | 0.006*** | **1.071*** ** | 0.006*** |
| *t-stat* | **3.43** | -0.99 | **3.48** | -1.39 | **3.94** | 3.99 | **3.21** | -2.87 | **3.27** | 1.64 | **2.99** | 3.02 | **3.95** | 3.76 |
| *MKT* | 0.104 | 0.001*** | 0.134 | 0.003*** | -0.004 | -0.006*** | 0.238** | | 0.226** | 0.000 | 0.226*** | -0.003*** | 0.096 | -0.002*** |
| *t-stat* | 1.20 | 4.67 | 1.33 | 4.24 | -0.04 | -9.78 | 2.26 | | 2.41 | 0.72 | 2.63 | -4.68 | 1.06 | -5.63 |
| *Size* | 73.137*** | | | | | | | 0.000 | | | | | | |
| *t-stat* | 5.03 | | | | | | | 0.90 | | | | | | |
| *low-high* | | 0.001** | | 0.001 | | -0.001* | | | | -0.000 | | 0.000 | | -0.001* |
| *t-stat* | | 2.14 | | 1.53 | | -1.83 | | -0.041*** | | -1.10 | | 0.10 | | -1.90 |
| *Low Leverage* | | | 26.353*** | | | | | -2.87 | | | | | | |
| *t-stat* | | | 2.83 | | | | | | | | | | | |
| *Low risk* | | | | | -34.332*** | | | | | | | | | |
| *t-stat* | | | | | -3.57 | | | | | | | | | |
| *Seasonality* | | | | | | | 38.550 | | | | | | | |
| *t-stat* | | | | | | | 0.76 | | | | | | | |
| *Skewness* | | | | | | | | | -28.098 | | | | | |
| *t-stat* | | | | | | | | | -1.33 | | | | | |
| *Momentum* | | | | | | | | | | | 1.169 | | | |
| *t-stat* | | | | | | | | | | | 0.10 | | | |
| *Profitability* | | | | | | | | | | | | | -51.561*** | |
| *t-stat* | | | | | | | | | | | | | -3.43 | |
| *Value* | | | | | | | | | | | | | | |
| *t-stat* | | | | | | | | | | | | | | |
| *Profit Growth* | | | | | | | | | | | | | | |
| *t-stat* | | | | | | | | | | | | | | |
| *Quality* | | | | | | | | | | | | | | |
| *t-stat* | | | | | | | | | | | | | | |
| *Investment* | | | | | | | | | | | | | | |
| *t-stat* | | | | | | | | | | | | | | |
| *Accruals* | | | | | | | | | | | | | | |
| *t-stat* | | | | | | | | | | | | | | |
| *Debt Issuance* | | | | | | | | | | | | | | |
| *t-stat* | | | | | | | | | | | | | | |
| Adjusted $R^2$ | 0.11 | 0.17 | 0.06 | 0.16 | 0.08 | 0.42 | 0.03 | 0.07 | 0.03 | 0.001 | 0.03 | 0.11 | 0.08 | 0.2 |
| *# Obs* | 335 | 335 | 335 | 335 | 335 | 335 | 335 | 335 | 335 | 335 | 335 | 335 | 335 | 335 |

Continued from previous page.

| | (15) | (16) | (17) | (18) | (19) | (20) | (21) | (22) | (23) | (24) | (25) | (26) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *low-high* | Value | *low-high* | Profit Growth | *low-high* | Quality | XBRL | Investment | *low-high* | Accruals | *low-high* | Debt Issuance |
| *Alpha (monthly %)* | **0.916***** | 0.006** | **0.817***** | 0.000 | **0.850***** | 0.004*** | **0.906***** | 0.004*** | **0.853***** | 0.001* | **0.615**** | 0.002*** |
| *t-stat* | **3.56** | 2.21 | **3.21** | 0.58 | **3.05** | 4.07 | **3.30** | 2.81 | **3.14** | 1.74 | **2.36** | 3.39 |
| *MKT* | 0.175* | -0.002*** | 0.223** | -0.000 | 0.217** | -0.001*** | 0.183** | -0.002*** | 0.236** | 0.000*** | 0.218** | -0.000 |
| *t-stat* | 1.75 | -2.86 | 2.39 | -0.12 | 2.46 | -3.38 | 2.00 | -3.66 | 2.29 | 3.00 | 2.31 | -0.19 |
| *Size* | | | | | | | | | | | | |
| *t-stat* | | | | | | | | | | | | |
| *low-high* | | -0.001 | | 0.000 | | -0.000 | | -0.000 | | -0.000 | | 0.000 |
| *t-stat* | | -1.28 | | 0.96 | | -0.38 | | -1.46 | | -1.14 | | 1.46 |
| *Low Leverage* | | | | | | | | | | | | |
| *t-stat* | | | | | | | | | | | | |
| *Low risk* | | | | | | | | | | | | |
| *t-stat* | | | | | | | | | | | | |
| *Seasonality* | | | | | | | | | | | | |
| *t-stat* | | | | | | | | | | | | |
| *Skewness* | | | | | | | | | | | | |
| *t-stat* | | | | | | | | | | | | |
| *Momentum* | | | | | | | | | | | | |
| *t-stat* | | | | | | | | | | | | |
| *Profitability* | | | | | | | | | | | | |
| *t-stat* | | | | | | | | | | | | |
| *Value* | -18.466** | | | | | | | | | | | |
| *t-stat* | -2.04 | | | | | | | | | | | |
| *Profit Growth* | | | 18.988 | | | | | | | | | |
| *t-stat* | | | 0.87 | | | | | | | | | |
| *Quality* | | | | | -6.274 | | | | | | | |
| *t-stat* | | | | | -0.37 | | | | | | | |
| *Investment* | | | | | | | -19.562 | | | | | |
| *t-stat* | | | | | | | -1.47 | | | | | |
| *Accruals* | | | | | | | | | -28.535 | | | |
| *t-stat* | | | | | | | | | -0.86 | | | |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Debt Issuance* | | | | | | | | | | | 119.196*** | |
| *t-stat* | | | | | | | | | | | 3.32 | |
| Adjusted $R^2$ | 0.04 | 0.09 | 0.03 | 0.001 | 0.03 | 0.05 | 0.03 | 0.13 | 0.03 | 0.04 | 0.06 | 0.03 |
| *# Obs* | 335 | 335 | 335 | 335 | 335 | 335 | 335 | 335 | 335 | 335 | 335 | 335 |

**Table 9 – Tangency portfolio Sharpe ratios**

This table reports the monthly Sharpe ratios of ex post tangency portfolios based on investing in the subsets of the *MKT* with each of the 13 factor clusters denoted as JKP Themes in Panel A1. Panel A2 reports the corresponding Sharpe ratios that adds *Complexity low-high* to the portfolios in A1. Panel B reports the Sharpe ratios of ex post tangency portfolios for Fama and French (*FF-5*, 2015) and Hou, Xue and Zhang (*q5*, 2015) factors along with *Easy – Complex*. Portfolio weights are normalized to sum to one. Avg. Returns and SD indicate the portfolio average returns and standard deviation respectively.

Panel A: Ex post Sharpe ratios for 13 factor-clusters

| | Panel A1: Tangency portfolio - *MKT* + Cluster | | | | | Panel A2: Tangency portfolio - *MKT* + Cluster + *low-high* | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | JKP Themes | *MKT* | SD | Avg. Returns | Sharpe Ratio | JKP Themes | *MKT* | *low-high* | SD | Avg. Returns | Sharpe Ratio | Incremental Sharpe ratio |
| *Size* | 0.00 | 1.00 | 4.41 | 0.77 | 0.13 | 0.00 | 0.37 | 0.63 | 2.51 | 0.62 | 0.17 | 0.04 |
| *Low Leverage* | 0.00 | 1.00 | 4.41 | 0.77 | 0.13 | 0.00 | 0.37 | 0.63 | 2.51 | 0.62 | 0.17 | 0.04 |
| *Low risk* | 0.41 | 0.59 | 2.04 | 0.52 | 0.17 | 0.28 | 0.38 | 0.33 | 1.67 | 0.52 | 0.20 | 0.04 |
| *Seasonality* | 0.87 | 0.13 | 0.68 | 0.20 | 0.02 | 0.76 | 0.11 | 0.13 | 0.71 | 0.24 | 0.08 | 0.06 |
| *Skewness* | 0.56 | 0.44 | 2.14 | 0.40 | 0.10 | 0.36 | 0.23 | 0.41 | 1.69 | 0.44 | 0.15 | 0.05 |
| *Momentum* | 0.45 | 0.55 | 2.45 | 0.57 | 0.16 | 0.27 | 0.33 | 0.40 | 1.96 | 0.55 | 0.19 | 0.03 |
| *Profitability* | 0.57 | 0.43 | 1.91 | 0.50 | 0.17 | 0.41 | 0.26 | 0.33 | 1.50 | 0.50 | 0.21 | 0.04 |
| *Value* | 0.39 | 0.61 | 2.73 | 0.58 | 0.15 | 0.22 | 0.33 | 0.45 | 2.03 | 0.56 | 0.18 | 0.04 |
| *Profit Growth* | 0.47 | 0.53 | 2.39 | 0.43 | 0.10 | 0.26 | 0.28 | 0.47 | 1.90 | 0.47 | 0.15 | 0.05 |
| *Quality* | 0.74 | 0.26 | 1.44 | 0.44 | 0.18 | 0.58 | 0.17 | 0.26 | 1.20 | 0.45 | 0.22 | 0.05 |
| *Investment* | 0.57 | 0.43 | 1.96 | 0.48 | 0.15 | 0.37 | 0.30 | 0.33 | 1.76 | 0.50 | 0.18 | 0.03 |
| *Accruals* | 0.73 | 0.27 | 1.52 | 0.30 | 0.08 | 0.51 | 0.17 | 0.33 | 1.38 | 0.37 | 0.13 | 0.05 |
| *Debt Issuance* | 0.87 | 0.13 | 0.92 | 0.26 | 0.08 | 0.73 | 0.11 | 0.16 | 0.98 | 0.30 | 0.12 | 0.04 |

Panel B: Ex-post Sharpe ratios for FF-5 and *q5* factors along with *Complexity low-high* portfolio

| | *MKT* | *SMB* | *HML* | *RMW* | *CMA* | *Easy – Complex* | SD | Avg. Returns | Sharpe Ratio |
|---|---|---|---|---|---|---|---|---|---|
| *FF-5* | 0.26 | 0.13 | 0.00 | 0.38 | 0.23 | | 1.28 | 0.407 | 0.171 |
| *FF-5* + (*Easy – Complex*) | 0.21 | 0.10 | 0.00 | 0.35 | 0.12 | 0.22 | 1.23 | 0.443 | 0.208 |
| | *MKT* | *ME* | *IA* | *ROE* | *EG* | *XBRL* | SD | Avg. Returns | Sharpe Ratio |
| *q5* | 0.21 | 0.13 | 0.15 | 0.05 | 0.46 | | 1.05 | 0.538 | 0.333 |
| *q5* + Acct. XBRL | 0.19 | 0.12 | 0.11 | 0.07 | 0.41 | 0.10 | 1.02 | 0.540 | 0.345 |

Figure 2: Ex-post Tangency portfolio Sharpe ratios for JKP factor-clusters and XBRL

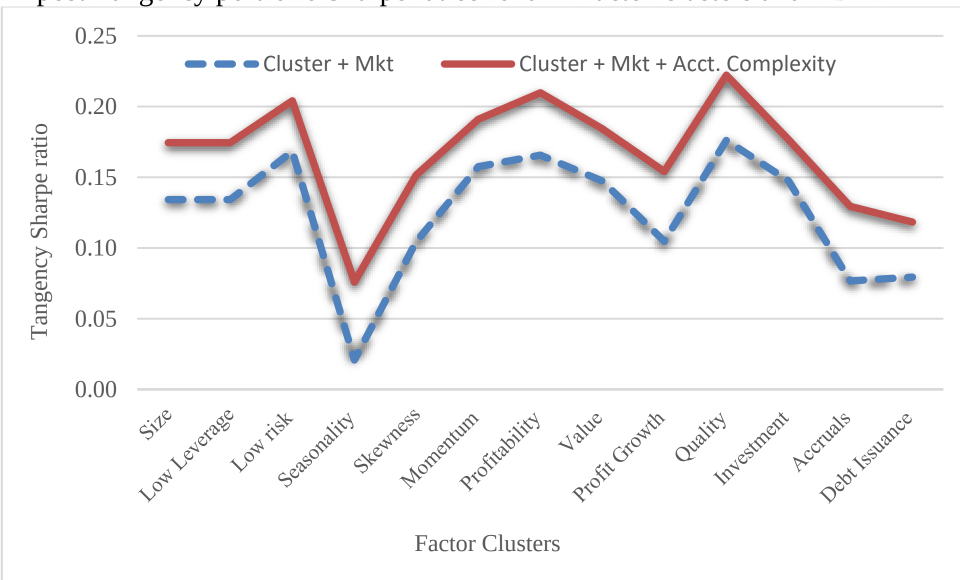

**Table 10 – Factor mimicking portfolio (FMP) tests.**

This table shows the regression results of the 15 value-weighted portfolios formed by double-sorting on size and *Complexity*. Each year firms are sorted based on *SIZE* into top 30%, middle 40%, and bottom 30% based on the NYSE breakpoints in each of the quintile *Complexity* portfolios. To classify the 15 portfolio combinations, we denote portfolios starting with S/M/L as those belonging to the Small/Medium/Large Size percentile. Similarly, the five *Complexity* quintile portfolios are denoted with $Q_1$, $Q_2$, $Q_3$, $Q_4$ and $Q_5$. We then define the returns for *MKTF* and *SIZEF* as *MKTF* = $(LQ_1 + LQ_3 + LQ_1 + LQ_3)/4$ and *SIZEF* = $(SQ_1+SQ_2+SQ_3+ SQ_4+SQ_5)/5$. The *COMPF*, portfolio is then defined as *COMPF* = *LOW* - *HIGH*, where *LOW* = $(SQ_1+ MQ_1+ LQ_1)/3$, and *HIGH* = $(SQ_5+ MQ_5+ LQ_5)/3$. We regress each of the 15 average portfolio returns on *MKTF*, *SIZEF* and *COMPF*. By construction, in each regression, we omit the returns of firms used on the left-hand side from the returns of firms on the right-hand side. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Corresponding t-statistics (indicated as t-stat) are presented in the adjacent row for each parameter.

| | SQ1 | SQ2 | SQ3 | SQ4 | SQ5 | MQ1 | MQ2 | MQ3 | MQ4 | MQ5 | LQ1 | LQ2 | LQ3 | LQ4 | LQ5 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Intercept | 0.003*** | 0.003*** | -0.001* | -0.002** | -0.003*** | 0.002* | 0.003* | 0.001 | 0.000 | 0.002 | -0.003 | 0.005*** | -0.001 | 0.004*** | 0.003*** |
| | 4.52 | 3.13 | -1.72 | -2.45 | -2.87 | 1.96 | 1.80 | 1.17 | 0.24 | 1.63 | -1.48 | 2.86 | -0.52 | 3.04 | 3.04 |
| *MKTF* | -0.106*** | 0.003 | 0.023 | -0.021 | 0.100** | 0.686*** | 0.751*** | 0.826*** | 0.726*** | 0.737*** | 1.255*** | 0.993*** | 1.233*** | 0.925*** | 0.999*** |
| | -3.02 | 0.06 | 0.67 | -0.53 | 2.04 | 11.35 | 8.84 | 14.51 | 12.67 | 13.09 | 11.76 | 12.46 | 13.69 | 13.98 | 19.25 |
| *SIZEF* | 1.002*** | 0.955*** | 1.009*** | 1.068*** | 0.966*** | 0.335*** | 0.310*** | 0.251*** | 0.341*** | 0.311*** | -0.309*** | -0.240*** | -0.278*** | -0.132** | -0.249*** |
| | 32.91 | 22.93 | 35.58 | 38.45 | 29.14 | 7.04 | 5.64 | 6.29 | 8.11 | 6.52 | -4.78 | -3.89 | -3.76 | -2.53 | -6.72 |
| *COMPF* | 0.415*** | 0.112** | 0.061 | -0.080** | -0.509*** | 0.125 | 0.027 | -0.162** | -0.285*** | -0.742*** | 0.363** | -0.286** | -0.327*** | -0.543*** | -0.846*** |
| | 9.07 | 2.20 | 1.57 | -2.00 | -8.89 | 1.54 | 0.23 | -2.08 | -5.04 | -9.20 | 2.51 | -2.37 | -3.59 | -8.53 | -13.48 |
| Adjusted $R^2$ | 0.97 | 0.95 | 0.97 | 0.97 | 0.96 | 0.90 | 0.90 | 0.93 | 0.93 | 0.92 | 0.79 | 0.62 | 0.81 | 0.79 | 0.85 |
| *# Obs* | 299 | 299 | 299 | 299 | 299 | 299 | 299 | 299 | 299 | 299 | 299 | 299 | 299 | 299 | 299 |

# Appendix

## Augmenting the FF5 risk factors with PIN and liquidity risk

It is well established that small-cap stocks usually suffer from risks from a lack of liquidity and risks due to high adverse selection. These stocks are also precluded from being held by some mutual funds which deprives them of an important source of liquidity. Therefore, as a logical extension of our sanity checks, we add proxies for these two types of risks in our base model.

A reasonable proxy for capturing adverse selection risk is provided by the probability of informed trading (*PIN*) which was first proposed by Easley, Keifer, O'Hara and Paperman (EKOP, 1996). Although the original *PIN* measures were estimated on an annual basis for a given stock, Easely et al. (2010) proposed a monthly *PIN* factor.[21] For an appropriate liquidity risk proxy, we turn to the Pastor-Stambaugh (PS, 2003) liquidity risk measure. Operationally, PS construct the measure, *PS_Liq*, as an equally weighted average of the liquidity measures of individual stocks on the NYSE and AMEX using daily data within a given month and following a similar approach as used by Fama and French (1993).

In Table 6, we augment our baseline model in Table 3 with the monthly *PIN* measure to see if the relative significance of our *XBRL premium* sustains. From Table 6 we find that the complaity *LOW-HIGH* monthly alphas are highly significant in each of the columns. For example, in Columns 1 through 4 we augment the FF5 factors with *PS_Liq*, *PIN* and *WML*. We find that the XBRL alphas range from 0.59% per-month to 0.61% and clears the t-stat threshold of 3.0 in each case. We also find that the adjusted $R^2$ improves from the base model and is an indication that the addition of *PIN* or *PS_Liq* does improve the explanatory power of the model. Importantly for us, however, alpha remains statistically significant, suggesting that XBRL *LOW-HIGH* portfolio captures distinct risk elements that are orthogonal to the liquidity or *PIN* or adverse selection risk.

Upon including *PS_Liq* in our base model, we observe that the coefficient of *PS_Liq* is positive and weakly significant, however we find the loading for *PIN* is negative and significant. When both factors are included in our base model, *PIN* continue to load negatively although weakly insignificant, while *PS_Liq* loses statistical significance. The regression $R^2$ at 0.26 is the highest among all iterations. We conclude that while introducing the two additional risk factors does indeed improve model explanatory power, the regression alpha, capturing *XBRL* risk, continues to be statistically significant.

**Table A1: Augmenting the *FF5* control factors with PIN and Liquidity factors.**

This table re-estimates Table 3 (baseline model) after controlling for probability of informed trading factor (*PIN*) of Easley, Hvidkjaer and O'Hara (2010) and liquidity factor (*PS_LIQ*) of Pastor and Stambaugh (2003). The first column reproduces the baseline model from Table 3 (the *LOW-HIGH* portfolio) with *PS_Liq*; the next column augments *PIN*; and the third column includes both the risk factors. Similarly, the fourth column augments *Momentum*. The '*Alpha*' represents the monthly risk-adjusted returns (in %) for the Low – High XBRL portfolios. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. Corresponding t-statistics (indicated as t-stat) for each coefficient are presented in the adjacent row.

[21] The authors constructed the monthly PIN factor for their 1984-2002 sample by first sorting the stocks into size deciles based on market capitalization at the end of the prior year and, within each size decile, formed three portfolios based on the PINs estimated over the prior year. Next, they calculated the average returns for the high and low PIN portfolios. Finally, they computed the monthly PIN factor as the difference in the portfolio returns between the high and low PIN portfolios.

| Long – Short portfolio (*Easy – Complex*) | | | | |
|---|---|---|---|---|
| | **(1)** | **(2)** | **(3)** | **(4)** |
| | ***PS_Liq*** | ***PIN*** | ***PIN* and *PS_Liq*** | ***PIN* and *PS_Liq* + *Momentum*** |
| ***Alpha (monthly %)*** | 0.594*** | 0.595*** | 0.578*** | 0.608*** |
| ***t-stat*** | 3.92 | 4.05 | 3.97 | 4.12 |
| *SMB* | 0.382*** | 0.477*** | 0.470*** | 0.487*** |
| *t-stat* | 5.81 | 7.99 | 7.98 | 7.80 |
| *HML* | -0.084 | -0.012 | -0.003 | -0.020 |
| *t-stat* | -1.22 | -0.16 | -0.04 | -0.27 |
| *RMW* | -0.076 | -0.016 | -0.028 | -0.024 |
| *t-stat* | -1.01 | -0.25 | -0.44 | -0.36 |
| *CMA* | -0.102 | -0.089 | -0.085 | -0.071 |
| *t-stat* | -1.01 | -1.07 | -1.05 | -0.84 |
| *MKT* | 0.013 | 0.017 | 0.006 | -0.015 |
| *t-stat* | 0.28 | 0.40 | 0.15 | -0.30 |
| *PIN* | | -0.224** | -0.229** | -0.242** |
| *t-stat* | | -2.42 | -2.46 | -2.53 |
| *PS_Liq* | 0.070* | | 0.050 | 0.064 |
| *t-stat* | 1.77 | | 1.32 | 1.50 |
| *Adjusted* $R^2$ | 0.21 | 0.25 | 0.26 | 0.26 |
| *# Obs.* | 300 | 300 | 300 | 300 |

## Accounting for trading costs

Few would disagree on the importance of estimating returns net of transactions costs since such costs can cut significantly into the returns, especially when trading in relatively illiquid stocks.[22] Since the impact of XBRL on portfolio excess returns is felt most significantly in small cap growth stocks, we believe that we should ensure that our excess returns are high enough to more than offset potential transactions costs and provide with economically meaningful net returns. With that in mind, we follow the method of Abdi and Ranaldo (2017) who use the easily available daily Close, High and Low (CHL) stock prices to estimate bid-ask spreads through combining Roll (1984) and Corwin and Schultz (2012). Abdi and Ranaldo recommend using two-day corrected effective spreads, which is what we use.[23] Specifically, we average the estimated effective spreads of all stocks in a given *XBRL* portfolio, for a given month, as a proxy for monthly portfolio level transactions costs.[24] Next, we calculate the portfolio

[22] Jones (2002), in a study of a century of stock market liquidity and trading costs, compiles an annual estimate of the weighted average commission rate for trading NYSE stocks over 1925-2000 where he defines the sum of half-spreads and one-way commissions, multiplied by annual turnover, as the estimate of the annual proportional cost of aggregate equity trading. Jones reports that the total costs average 0.84% over the 1925-2000 period. He also holds that total costs have actually been below 0.50% since 1991. Taking this value as the baseline transactions cost estimate puts our net annual excess returns of our *Complexity* portfolios as being significantly positive.

[23] For robustness, in unreported tests we also estimate Hasbrouck (2009) trading costs, that come from the estimation of a random-walk model of stock prices. However, we find Abdi and Ranaldo (2017) average trading cost measure is higher relative to that of Hasbrouck (2009). Therefore, as a conservative approach we report only the results accounting for Abdi and Ranaldo (2017) trading costs. Our results remain strong when we use Hasbrouck's measure as well.

[24] To ensure our estimates are comparable to those reported by Abdi and Ranoldo (2017), we perform benchmarking checks as follows. We calculate the average (and median) *CHL* for the 2003 through 2015 sample, identical to those reported by Abdi and Ranoldo (2017) in their Table 3 (p.4456). We find that our average trading

level monthly stock returns *net of* transactions costs which forms our new dependent variable across the three *XBRL* portfolios and re-estimate our base model.

Table 8 reports our findings. We see that *LOW-HIGH* portfolio monthly alpha drops from 0.73% to 0.46% in the quintile sort, which translates to an annualized difference of approximately 0.65%. Similarly, in decile sort the *LOW-HIGH* portfolio monthly alpha drops from 0.90% monthly to % monthly. Not surprisingly, the portfolio alphas drop relative to our baseline estimates, however it is noteworthy that even after incorporating a reasonable proxy for transactions costs, we continue to see significantly positive alphas associated with *Complexity* portfolio.

**Table A2: Accounting for Transaction Costs – Abdi and Ranoldo (2017) measure**

This table re-estimates Table 3 net of trading costs consistent with Abdi and Ranoldo (2017) approach. To calculate the monthly trading cost for every firm-month, we first calculate the percentage spread estimates (identified as *CHL* or *Close-High-Low*) based on the two-day corrected approach (Eq. 11) in section 1.2 (page 4,447-4,448) of Abdi and Ranoldo (2017).Next, we form the low-high value-weighted portfolios, sorted on *Complexity* into quintiles or deciles, identified as *Easy* (Q1 of *XBRL*) and *Complex* (Q5 or D10 of *XBRL*). The '*Alpha*' represents the monthly risk-adjusted returns (in %) for the low-high (*Easy* – *Complex*) *Complexity* portfolios. "# Stocks" shows the average number of stocks in the portfolio. Asterisks ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The corresponding t-statistics (indicated as *t-stat*) are presented in the adjacent row for each parameter.

| Parameter | Quintile - Sort | | Decile - Sort | |
|---|---|---|---|---|
| | Long – Short portfolio (*Easy* – *Complex*) | | | |
| | (1) | (2) | (3) | (4) |
| | FF5 | FF5 + Momentum | FF5 | FF5 + Momentum |
| ***Alpha (monthly %)*** | 0.457*** | 0.483*** | 0.649*** | 0.700*** |
| ***t-stat*** | 3.04 | 3.18 | 2.97 | 2.85 |
| *SMB* | 0.405*** | 0.417*** | 0.663*** | 0.686*** |
| *t-stat* | 6.26 | 6.35 | 6.30 | 5.91 |
| *HML* | -0.092 | -0.110 | -0.158 | -0.194* |
| *t-stat* | -1.35 | -1.58 | -1.62 | -1.97 |
| *RMW* | -0.055 | -0.049 | 0.099 | 0.110 |
| *t-stat* | -0.71 | -0.62 | 0.88 | 0.90 |
| *CMA* | -0.110 | -0.098 | 0.012 | 0.036 |
| *t-stat* | -1.09 | -0.94 | 0.09 | 0.28 |
| *MKT* | 0.023 | 0.007 | 0.120 | 0.088 |
| *t-stat* | 0.50 | 0.15 | 1.32 | 1.14 |
| *WML* | | -0.055 | | -0.108 |
| *t-stat* | | -0.95 | | -1.05 |
| *Adjusted $R^2$* | 0.202 | 0.20 | 0.14 | 0.14 |
| *# Obs.* | 335 | 335 | 335 | 335 |

costs are almost identical to those reported by them. For example, these authors report a mean (median) spread of 1.39% (1.03%) in their 2003 through 2015 sample. In comparison, we find a mean (median) spread of 1.40% (1.03%) over the same sample period. Over our longer sample, we find the mean (median) CHL spreads to be 1.04% (0.88%), all of which compare favourably with their reported findings.