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Size and Book-to-Market: Comparing Factor Loadings, Characteristics, Methodologies, and Time Periods

Tim Mooney

Abstract

We show new evidence of firm size and book-to-market as priced risk factors in an empirical asset pricing model. A robust size and value premium persists across 1963-1991 and 1992-2017 sub-samples. Characteristics-based models do a better job explaining variation in stock returns than models based on factor loadings. An instrumental variable approach using individual stocks as test assets performs better than one using portfolios. We also present a decile-based measure of size and value with risk premium estimates that are intuitive to interpret. Results have implications for how investors might better understand exposure to systematic risk factors.

I. Introduction

In attempting to explain the tremendous variation in stock returns, many researchers have focused on empirical evidence of common risk factors. The two most prominent factors are the size effect, where stocks with lower market capitalizations tend to have higher returns, and the value effect, where value stocks—typically defined in the literature by high book-to-market ratios—also have higher returns. A common view is that these higher returns are compensation for bearing more systematic risk, made immensely popular in the literature by Fama and French in their 1992, 1993, and 1996 studies. The discussion of size and value is still ongoing. Some researchers find that these risk premia are transient through time (Huang and Huang, 2013) or are gone completely (e.g., Horowitz, Loughran, and Savin, 2000; van Dijk, 2011 for the size premium). Other studies find that the factors are not correctly specified or measured, as Novy-Marx (2013) shows how gross profitability confounds the value effect, while some parameter specifications do not affect overall results, as Krueger and Johnson (1991) find. Still others argue that the reported size and value effects are artifacts of the methodology employed. Despite this discord, the original articles are heavily cited in finance literature. As of 2019, the seminal group of papers by Fama and French have almost 50,000 citations. Moreover, "smart beta" investments based on the size and value effects (among others) are increasingly being marketed to individual investors (Kahn and Lemmon, 2016). Clearly, the persistence of these risk factors in finance literature and investment practice warrants additional investigation into their methodology and robustness.

In this study, we take a closer look at size and value as priced risk factors in the cross-section of stock returns. We compare a widely cited empirical asset pricing model, the Fama French three-factor model, with a model based on actual firm characteristics as in Daniel and Titman (1997). Although size and book-to-market have been heavily studied in their ability to explain stock returns, we add to existing literature in a few areas. First, a substantial amount of time has passed since Fama and French's original studies of 1992, 1993, and 1996, providing nice pre- and post-publication sample periods to evaluate size and book-to-market. The original papers looked at stock returns around 1963-1991, about 340 months. We examine that period and compare

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it to the period 1992-2017, about 300 months. In contrast with some studies, we find significant size and value premia over both sub-samples and for the overall 1963-2017 period.

Second, we provide further insight into why size and book-to-market explain returns in the first place. Fama and French argue that regression slopes on their factor-mimicking portfolios SMB and HML proxy for common priced risk factors—stocks with high factor loadings on SMB are more sensitive to business cycle swings, which seems reasonable since small firms would ostensibly have the same sensitivity. Similarly, Fama and French argue that high HML loadings proxy for firm distress, where weaker firms with persistently low profitability have high book-to-market ratios, which practitioners would term value stocks. A natural question follows from this: why not just use a firm's actual size and book-to-market to explain stock returns, rather than regression slopes from factor-mimicking portfolios? Daniel and Titman (1997) first examine this question, and they argue that size and book-to-market as firm characteristics are favorable over factor loadings. We thoroughly compare the characteristics-based model to the Fama French three-factor model and provide new evidence that actual firm characteristics explain stock returns more robustly than SMB and HML factor loadings. In addition, we use size and book-to-market deciles as explanatory variables, and these provide estimates of size and value premia that are intuitive to interpret and also comparable across sub-sample periods. Holding other factors constant, a one-decile increase in firm market capitalization is associated with decrease in excess return of about 8 basis points. For value, a one-decile increase in book-to-market is associated with an excess return that is about 7 basis points higher.

Third, we use consistent econometric methodologies to analyze the two models. Fama and French (1992) utilize the Fama and MacBeth (1973) two-pass approach with size and book-to-market, but their regressions do not actually include the three-factor model. Fama and French (1993, 1996) look at 25 sets of factor loadings (i.e., regression coefficients), one for each of the 25 portfolios formed on size and book-to-market, but they do not utilize the Fama-MacBeth approach. They stress that the time-series statistical significance and patterns among the 25 portfolio factor loadings combine to make their model compelling. Daniel and Titman (1997) use a similar approach, but with nine portfolios. We conduct both time series and Fama-MacBeth analysis for the Fama French three-factor model and the characteristics-based model, with consistent methodology that allows for more direct comparison between the two models.

Finally, we employ a recent approach to resolving the errors-in-variables problem endemic to the Fama-MacBeth methodology. The second stage of the Fama-MacBeth approach uses estimated regression coefficients as data, and because such coefficients are estimated with sampling error, second stage risk premium estimates will be biased and inconsistent in the presence of correlated sampling errors. Fama and MacBeth (1973) address this by forming portfolios. Portfolios are less prone to errors-in-variables bias but can confound results, as documented by Lo and MacKinlay (1990) and Jegadeesh (1992), among others. In contrast, Jegadeesh et al. (2019) circumvent potential errors-in-variables bias with an instrumental variable approach using individual stocks. We compare the Fama French three-factor model to the Daniel and Titman characteristics-based model using both the portfolio-based approach and Jegadeesh et al.'s instrumental variable approach. Models that employ instrumental variables and individual stocks as test assets perform better than the more commonly-used portfolio methodology.

To our knowledge, this study is the first to analyze and compare the three-factor model and the characteristics-based model along all of these dimensions. In doing so, we hope to clarify what the model can explain and provide insight into why size and book-to-market have explanatory power over stock returns. Overall, the Daniel and Titman characteristics-based model provides more robust evidence of the size and value premia than the Fama French three-factor model, and premia estimated using the characteristics-based model are also more intuitive to interpret, especially when using a stock's size and book-to-market deciles as explanatory variables.

To be sure, size and value do not completely explain cross-sectional variation in stock returns. Researchers have presented evidence of other priced risk factors such as momentum, profitability, investment, and over 300 others (Harvey, Liu, and Zhu 2016). Our aim here is not to present a parsimonious model that fully explains stock returns. Rather, we focus on size and value because they are prominent and relatively simple to understand. Analysis of this simpler model could help individual investors make more informed decisions about risk factor exposures in their portfolios.

The rest of this paper proceeds as follows. Section II briefly reviews relevant literature and motivates our empirical approach. Section III describes data and methodology. Section IV contains summary statistics. Section V presents the main empirical results. Section VI addresses robustness, and Section VII concludes.

II. Literature review

Seminal papers

Before empirical asset pricing models were devised to explain systematic risk factors related to size and book-to-market, researchers first discovered that such stocks earned higher returns. Banz (1981) and Keim (1983) documented that smaller firms earned positive abnormal returns, and Stattman (1980) and Rosenberg, Reid, and Lanstein (1985) found evidence that firms with higher book-to-market ratios—or to practitioners, lower price-book ratios—did as well. Basu (1983) finds evidence of the value effect with firm earnings-price ratios. These anomalies, among others, fueled the debate over market efficiency, the legitimacy of existing theoretical asset pricing models such as the CAPM, and the inability to assess simultaneously market efficiency and the validity of an asset pricing model (e.g., Roll, 1977). This study does not focus not on that debate, but rather on the empirical asset pricing models that followed.

Given the documented size and value anomalies and the inability of theoretical asset pricing models to explain observed anomalies thoroughly, Fama and French developed an empirical model that included size, value, and also a market factor (beta). Their approach would become heavily cited and widely adopted and debated in finance literature. Fama and French (1992) use the Fama-MacBeth methodology to evaluate size, book-to-market, and the market factor; however, in that study they do not include a regression with all three factors at once. To address the errors-in-variables problem caused by using beta as a regressor, Fama and French form portfolios based on firm size and beta and assign each stock the beta of its corresponding portfolio.

Fama and French (1993) formalize the three-factor model and move away from the Fama-MacBeth methodology. Instead, their evidence is based on time-series regressions of 25 portfolios formed according stocks' size and book-to-market quintiles. Their main explanatory variables are returns from factor-mimicking portfolios: SMB, the difference between the return on small cap stocks and large cap stocks, and HML, the difference between stocks with high (value stocks) and low (growth stocks) book-to-market ratios. Fama and French claim that the statistical significance of the regression coefficients on SMB and HML provide evidence that variation in size and book-to-market help explain stock returns. In addition, they cite the variation in the magnitude of the coefficients across portfolios as further support for this claim. For example, in their study the coefficient on SMB is higher for smaller size quintiles across all book-to-market quintiles. In other words, even after controlling for variation in book-to-market, small stocks tend to be more sensitive to SMB than larger stocks. Similarly, factor loadings on HML increase as book-to-market increases, across almost all size quintiles. Finally, Fama and French claim that the three-factor model does not leave significant variation in stock returns unexplained, as time-series intercepts from regressions for 22 out of 25 portfolios have t-statistics less than 2. Fama and French have been prolific in expanding upon the original findings involving the three-factor model, producing numerous subsequent studies in the areas of additional factors, evaluating anomalies, international evidence, investment opportunities, and other areas (see, e.g., Fama and French, 1996, 1998, 2017).

Characteristics vs. covariances

The Fama French three-factor model is based on portfolio covariances with returns on SMB and HML, and the authors argue that these covariances capture variation in stock returns due to size and value risk factors. Daniel and Titman (1997) counter Fama and French's argument by claiming that actual firm characteristics of size and book-to-market explain stock returns rather than covariances with factor-mimicking portfolios. Daniel and Titman support this claim by forming portfolios based on stock characteristics and factor loadings. They show that firms with similar characteristics but different factor loadings do not have different returns, in contrast to the Fama French three-factor model's prediction. Specifically, they show that the higher returns of small cap stocks and value stocks cannot be explained by SMB and HML factor loadings. They also report that after controlling for size and book-to-market, market beta does not have explanatory power over stock returns. Several studies have examined what specifically about size and value makes them priced risks for stocks. Krueger and Wrolstad (2012, 2013) find robust relationships between fundamental-based portfolio weightings and returns, particularly with ratios based on cash flows. The authors also find that reputation may be a driving force, as they find reputation measures have predictive power for risk-adjusted returns (Krueger and Wrolstad 2016).

Methodology: portfolio sorting vs. individual stocks

Grouping stocks into portfolios is a central component of most empirical asset pricing investigations, for a few reasons. The most prominent relates to the way asset pricing models are tested. In many cases, researchers use the two-stage methodology of Fama and MacBeth (1973). First, one estimates time-series stock return sensitivity to some factor such as the overall market return. The second stage is cross-sectional, where for a given time period stock returns are regressed on the factor sensitivity (beta) from the first stage. Because a coefficient estimate like beta is only a sample estimate of a population parameter and is thus susceptible to sampling error, there is potential for errors-in-variables bias when using betas as data in a regression. Blume (1970) points out that if sampling error for betas in a given portfolio are independent, then portfolio betas should be less subject to errors-in-variables bias. Fama and MacBeth extend Blume's assertion to beta sampling errors that "are substantially less than perfectly positively correlated."

However, multiple studies have pointed out that sorting stocks into portfolios can yield spurious and misleading results. Lo and MacKinlay (1990) show that sorting stocks into portfolios can impart data-snooping bias. Berk (2000) argues that tests run on sorted portfolios are prone to bias. Jegadeesh (1992) shows how portfolios formed with very high correlations between size and market beta can lead to spurious results, and he finds that after controlling for size, market beta explains almost no variation in stock returns. Kim (1995) illustrates that the errors-in-variables problem can be present even in portfolio betas. Ferson, Sarkissian, and Simin (1999) show how portfolio sorting can produce a convincing case in favor of a factor model even if a factor is completely made up and has no actual relation to systematic risk. Daniel and Titman (2012), Daniel, Titman, and Wei (2001), and Lewellen, Nagel, and Shanken (2010) also raise issues with factor model testing involving portfolios.

Researchers have proposed varied solutions to the problems associated with portfolio sorting. Litzenberger and Ramaswamy (1979) and Kim (1995) propose methodologies to correct errors-in-variables bias based on maximum likelihood estimation. Brennan, Chordia, and Subrahmanyam (1998) use risk-adjusted returns for individual stocks, obviously avoiding issues related to portfolio returns, and they also argue that risk adjustment sidesteps the errors-in-variables issue, since returns properly adjusted for risk factors should be independent of other stock characteristics.

Most relevant to this study, Jegadeesh et al. (2019) combine the Fama-MacBeth methodology with an instrumental variable approach using individual stocks as test assets instead of portfolios. To address potential errors-in-variables bias, the authors estimate time-series factor sensitivities for even months and odd months. For the cross-sectional stage, regressions are estimated for even (odd) months using the odd-month (even-month) betas as instruments. Jegadeesh et al. contend that because independent variables (e.g., even-month betas) are estimated from a different sample of data than instrumental variables (e.g., odd-month betas), their sampling errors should be uncorrelated. Jegadeesh et al. prove the consistency of their instrumental variable estimator, and they show it estimates true risk premia accurately using simulation results.

III. Data, sample and methodology

The sample period for this study is January 1963 to June 2017. We obtain stock return data from CRSP for stocks listed on the New York Stock Exchange, NASDAQ, and AMEX. Following existing literature, financial firms (SIC codes 6000-6999), utilities (SIC codes 4910-4939), American Depositary Receipts, closed-end funds, preferred stocks, real estate investment trusts, and stocks with a price of less than $1 are excluded. Following Jegadeesh et al. (2019), we exclude stocks with return data for fewer than 200 trading days in a given year. Data for the book value of equity come from COMPUSTAT. Book value of equity is computed as stockholder's equity plus deferred taxes and investment tax credit, minus preferred stock. We exclude firms whose book value of equity is negative. When computing a firm's book-to-market, we use the last available figure for book value of equity in year *t-1* and market value of equity (price times shares outstanding from CRSP) as of the end of year *t-1*. We measure size as market value of equity in June of year *t*. We then use those size and book-to-market figures for analysis from July of year *t* through June of year *t+1*. Factor-mimicking portfolio returns SMB and HML, market returns, the risk-free return, and portfolio size and book-to-market breakpoints all come from Kenneth French's website.[1] SMB is the return for stocks with market capitalizations below the NYSE median market cap minus the return for stocks with market caps above the NYSE median. HML is the return for high book-to-market stocks (with a ratio at or above the NYSE seventieth percentile) minus the return for low book-to-market stocks (with a ratio at or below the NYSE thirtieth percentile).

We use the Fama and MacBeth (1973) two-stage method to evaluate size and value as priced risk factors in an empirical asset pricing model. The first stage estimates time-series regression coefficients of an asset excess return *r* on risk factors, where each asset is a stock or portfolio *i*. The second stage involves cross-sectional regressions of asset excess returns on estimated betas from the first stage, for each month *t*. The average second-stage coefficients are the risk premium estimates for the factors in the model. For the Fama French three-factor model, the two stages are represented by Equations (1) and (2):

$$r_{i,t} = a_0 + \beta_{1,i} MKT_t + \beta_{2,i} SMB_t + \beta_{3,i} HML_t + \varepsilon_{i,t} \tag{1}$$

$$r_{i,t} = \gamma_0 + \gamma_1 \hat{\beta}_{1,i} + s_i \hat{\beta}_{2,i} + h_i \hat{\beta}_{3,i} + \xi_{t,i} \tag{2}$$

Where $r_{i,t}$ is the excess return of asset *i* in month *t*; MKT_t, SMB_t, and HML_t are the returns on the market, SMB, and HML, in month *t*; and s_i and h_i are the factor loadings on SMB and HML for asset *i*. Equations 3 and 4 show the two stages for the Daniel and Titman characteristics-based model:

$$r_{i,t} = a_0 + \beta_1 MKT_t + \varepsilon_{i,t} \tag{3}$$

$$r_{i,t} = \gamma_0 + \gamma_1 \hat{\beta}_{1,i} + \gamma_2 SIZE_i + \gamma_3 BM_i + \xi_{t,i} \tag{4}$$

Where $SIZE_i$ and *BMi* are the size and book-to-market for asset *i*.

For part of our analysis, we follow the instrumental variable approach of Jegadeesh et al. (2019), to address potential errors-in-variables bias in the second stage of Fama-MacBeth analysis. In the first stage, we estimate betas for even and odd months separately, using daily stock and market returns for months *t-36* to *t-1* to estimate betas in month *t*. In the second stage, we estimate cross-sectional regressions for even (odd) months using odd-month (even-month) betas as instruments. Note that size and book-to-market are observed rather than estimated and thus are not prone to errors-in-variables bias. Risk premium estimates are then the average of the even-month and odd-month second stage regression coefficients. Results are very similar when using weekly or monthly stock returns to estimate first-stage betas, and also when using one or five years of historical returns instead of three.

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[1] Like so many others, we are grateful to Professor French for generously making this data publicly available at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/index.html.

IV. Summary statistics and comparison to existing literature

Table 1 presents summary statistics for the two sub-sample periods: the original Fama French sample period of July 1963-December 1991, and the subsequent period January 1992-June 2017. A few differences across the two periods are evident. First, the mean monthly excess stock return was 35.7 basis points higher in 1992-2017 compared with 1963-1991. Cross-sectional stock return variability increased as well, from 13.8% to 16.9%—although not reported in the table, the difference between sub-sample standard deviations is significant at the 1% level. Also, firm size measured by market capitalization has increased substantially and become much more dispersed. The average book-to-market ratio has declined, reflecting a number of possible drivers, including the potential for higher growth expectations due to technological advances, increased use of share repurchases, and increased demand for stock driven by much broader investor participation in the stock market. In addition, the mean number of stocks also increased by several hundred, although the number of listed companies varies by year within each sub-sample.

The factor-mimicking portfolio returns are positive. The mean return for SMB is 0.266 (0.167) percent per month during 1963-1991 (1992-2017), indicating that smaller stocks with market caps below the NYSE median have higher returns than stocks with above-median market caps. The mean return for HML is 0.392 (0.301) percent per month during 1963-1991 (1992-2017), which suggests value stocks with book-to-market ratios above the NYSE seventieth percentile have higher returns than growth stocks with book-to-market ratios below the NYSE seventieth percentile. Average factor-mimicking portfolio returns are not significantly different across the two sub-samples. Factor loadings are also positive—on average, stock excess returns are positively related to returns for SMB and HML. However, the average SMB factor loading has declined significantly, from 1.029 during 1963-1991 to 0.888 during 1992-2017. This accords with the debate in literature over the existence and magnitude of the size premium over time. Although the difference between the two sub-samples for the HML factor loading is statistically significant, the economic significance appears limited. Overall, across the sample period firms have grown larger and returns have increased and become cross-sectionally more volatile. However, despite tremendous changes in financial markets and the environment in which listed firms operate over the entire sample period, the evidence appears consistent with a size and value premium, at least on a univariate basis.

As a first attempt at incorporating multiple factors associated with stock returns, we use the familiar portfolio double-sorting methodology popularized by Fama and French. Although the vulnerabilities of portfolio sorting are detailed in Section II above, their widespread use make them a common reference point of comparison to other studies. Table 2 presents mean monthly excess returns for portfolios sorted into quintiles along two different sets of dimensions. First, portfolios are sorted by size and book-to-market quintiles, consistent with Fama and French (1993). We also sort portfolios into quintiles according to their factor sensitivities to SMB and HML, similar to Daniel and Titman (1997) and Daniel, Titman, and Wei (2001). Panel A covers July 1963 to December 1991, and Panel B covers January 1992 to June 2017.

From Fama and French's size and book-to-market sorts, we see familiar evidence to support these firm attributes as priced risk factors in the 1963-1991 sub-sample. Looking at each book-to-market quintile column, we see that stocks in lower size quintiles tend to have higher excess returns, with the exception of the lowest book-to-market quintile. This evidence is consistent with the size effect. For each size quintile row, returns show an overall pattern of increasing when moving from low book-to-market quintiles (growth) to high quintiles (value). In the later 1992-2017 sub-sample, these patterns are not as consistent; it appears that smaller size quintiles do not always have higher returns, and the value effect is not evident in the two largest size quintiles.

Turning to portfolios sorted by SMB and HML factor loadings, it is important to clarify that the SMB loading quintiles are presented in descending order, as quintile 5—with the highest sensitivity to SMB—contains stocks that behave most like small cap stocks, and quintile 1 would be made up of large cap-like stocks. Here, results are more ambiguous. Patterns of higher returns for higher SMB factor loading quintiles (smaller stocks) and higher HML loading quintiles (value-like stocks) are not as strong, and results are especially mixed in the later 1992-2017 sub-sample. The contrast between these two sorting methodologies suggests that the firm characteristics size and book-to-market and factor sensitivities to SMB and HML are not measuring the same thing.

V. Analysis with individual stocks

Next, we shift away from portfolio returns and instead use the Fama and MacBeth (1973) method with individual stocks. As described above, in order to address potential errors-in-variables bias as well as avoid the empirical limitations of using portfolios we follow the instrumental variable approach of Jegadeesh et al. (2019). Our main interest is comparing risk premium estimates and significance using factor-mimicking portfolio returns SMB and HML to results using actual characteristics of firm size and book-to-market.

Table 3 presents second stage risk premium estimates for the Fama French three-factor model using individual stocks, estimating Equation 2. Results here are not as compelling as earlier evidence involving portfolio sorts. The size premium measured by sensitivity to the return on SMB is insignificant in both sub-samples as well as for the whole sample period. The value premium measured by the sensitivity to HML is significant in the 1963-1991 sub-sample and for the whole sample. For the whole sample, a one-unit increase in a stock's HML factor loading is associated with a 39.8 basis point increase in monthly excess return, other things equal. Although this quantifies the value premium, the fact that it is based on a rather abstract HML factor loading makes its interpretation complicated and unclear. Market beta is negative but insignificant. The average R-squared of 2.9-3.2% highlights the noise in the cross-section of expected stock returns, even when using models that have strong time-series explanatory power.

Next, we evaluate size and value using actual firm characteristics. As above, we include a stock's market beta estimated using the instrumental variable approach of Jegadeesh et al. (2019). Table 4 presents estimation results for Equation 4, showing risk premium estimates using individual stocks. Results show robust size and value premia. The sign of the coefficient on size is negative and significant, consistent with expectations. Because size is measured as the natural log of market cap, interpreting the coefficient merits clarification: based on the full sample, a one-unit increase in log market cap—for example, a change in market cap from \$1.1 billion to \$3.0 billion—is associated with a 12 basis point decrease in monthly excess stock return. The coefficient on book-to-market is positive and statistically significant at 0.144 for the full sample. A one-unit increase in book-to-market ratio is associated with a 14.4 basis point increase in monthly excess return. The coefficients on size and book-to-market are statistically significant for the two sub-samples as well as the full sample period. As with the Fama French three-factor model using individual stocks above, market beta is insignificant, consistent with Jegadeesh et al. (2019). Intercepts are positive and significant in all specifications, indicating that beta, size, and value leave a significant portion unexplained in the cross-section of stock returns, as expected. Average adjusted R-squared for the characteristics-based model is slightly higher than the Fama French three-factor model above but still low at around 3.1-3.9%.

To sum up the results in Tables 3 and 4, a model based on actual firm characteristics of size and book-to-market provides more consistent evidence of the size and value effects than one based on factor-mimicking portfolio regression slopes. The characteristics-based model also has explanatory variables that are easier to understand than the more abstract factor loadings of the three-factor model. However, as mentioned above the use of log-transformed firm size makes interpreting the economic impact of the model coefficient estimates cumbersome.

Thus, we also estimate risk premia for individual stocks using their size and value deciles as explanatory variables. Each year stocks are assigned to deciles based on their size and book-to-market. Using a relative measure like deciles is particularly useful when firm characteristics change throughout the sample period, as they do here. For example, the impact of a $200 million increase in market cap for the average-sized firm would be far greater in the 1960s compared to recent years. In contrast, a one-decile change captures variation relative to other firms at a given point in time. We will also see that these models yield coefficient estimates with an intuitive interpretation.

Table 5 presents risk premium estimates for the Fama French three-factor model using SMB and HML factor loading deciles as explanatory variables, and significance for SMB and HML is still mixed. For the 1963-1991 sub-sample, coefficients on the SMB and HML factor loading deciles are positive and significant. Interpreting the coefficient estimates is straightforward: a one-decile change in a stock's SMB (HML) factor loading is associated with an 7.7 (3.9) basis points increase in monthly excess stock return, other things equal. However, understanding a stock's factor sensitivity is not very intuitive, especially for the average investor. Moreover, these coefficients are insignificant in the later sub-sample, and across the entire sample period only the SMB decile is significant. When using factor loading deciles, market beta is negative and statistically significant, in contrast to the negative but insignificant beta when actual factor loadings are used as in Table 3. Intercepts remain positive and significant, and R-squared is still low at around 2-3%.

Table 6 shows risk premium estimates for the characteristics-based model with firm size and book-to-market deciles as explanatory variables, and again the model shows consistent size and value risk premia. The coefficient on a firm's size decile is negative and significant in the two sub-samples as well as for the whole sample. Interpreting the decile coefficients is quite intuitive: for the whole sample, a one-decile increase in firm size—for example, going from the 20th to the 30th percentile in market cap—is associated with an 8.3 basis point decrease in monthly excess stock return. The coefficient on book-to-market is also consistently positive and significant; for the whole sample, a one-decile increase in a firm's book-to-market ratio is associated with a 6.5 basis point increase in monthly excess return.

In comparing the results in Tables 3 through 6, the evidence suggests that actual firm characteristics of size and book-to-market consistently capture covariation in the cross-section of stock returns, whereas factor loadings on SMB and HML do not reliably do so. Thus, it appears that a stock's SMB and HML factor loadings do not measure the size and value effects as well as a firm's size and book-to-market ratio.

VI. Robustness

For completeness, we estimate size and value risk premia using portfolios rather than individual stocks. First, we test the Fama French three-factor model using 100 portfolios of stocks formed according to their size and book-to-market deciles. We use 100 portfolios instead of 25 to increase the cross-sectional sample size, as results with only 25 portfolios are largely insignificant. We use the same Fama-MacBeth methodology to estimate size and value risk premia. Table 7 presents these results, which are qualitatively similar to results for individual stocks in Table 3. In Table 7, market beta is negative but marginally significant. The size premium is also insignificant. The value premium is positive and significant for the 1963-1991 sub-sample period and for the whole sample, but it is insignificant in the 1992-2017 sub-sample. Notably, using portfolios instead of stocks as test assets increases R-squared markedly to around 23%, compared with 2-3% when using individual stocks. As with all models in this study, intercepts are positive and significant.

Next, we test the Daniel and Titman characteristics-based model with portfolios. We sort stocks into 100 portfolios based on their SMB and HML factor loading deciles. Table 8 presents risk premium estimates and show a significant but volatile size effect, with coefficients varying from -0.269 to -1.325, well beyond what would seem to be a reasonable magnitude for the size effect. The average book-to-market coefficient also varies across the two sub-samples, between 0.897 for 1963-1991 and -0.019 for 1992-2017. The limited significance of the size and value premia estimates from Tables 7 and 8 suggests that using portfolios instead of individual stocks may be confounding results, as Lo and MacKinlay (1990), Berk (2000), and several others have pointed out.

VII. Conclusion

In this study, we find new robust evidence of both the size and value premia, even after controlling for market risk. These premia persist across sub-sample periods, in contrast with other studies that find the size effect transient through time. This study is also the first of our knowledge to use thorough, consistent methodology to compare the Fama French three-factor model to a model based on firm characteristics, using both portfolios and individual stocks as test assets. A characteristics-based model with firm size and book-to-market ratio explains variation in stock returns due to size and value better than the Fama French three-factor model. Risk premium estimates are statistically significant, reasonable, and intuitive to interpret, particularly for risk premium estimates based on size and value deciles. Consistent with other studies, market beta does not have explanatory power over cross-sectional stock returns after taking into account size and book-to-market. Our main analysis avoids the empirical pitfalls associated with portfolio sorts and potential errors-in-variables bias. To do this, we use individual stocks as test assets and employ an instrumental variable approach to address any potential errors-in-variables bias.

Clearly, size and book-to-market along with the overall market factor are not sufficient to explain variation in stock returns. That is not the intent of this study. Instead, we contribute new evidence to existing literature in support of a size and value effect. Moreover, the size and value premia can be quantified in relatively simple terms. For size, a one-decile increase in firm market capitalization is associated with an excess return that is about 8 basis points lower, after controlling for value and the market return. For value, a one-decile increase in book-to-market is associated with an increase in excess return of about 7 basis points, other things equal. Again, these risk premia are stable across sub-sample periods. Practitioners may find this result of interest when advising individual investors about how they might be rewarded for bearing different kinds of risk. Beyond a simple discussion of diversification and market risk, exposure to the priced risks of small stocks and value stocks can provide higher average excess returns. Future research could expand on these results by testing realistic investment strategies for individual investors that are designed to capture the size and value risk premia, such as long-only exposure to small cap stocks and value stocks. In addition, further exploration of how these premia are sensitive to seasonal factors such as those of Krueger (1990) could clarify the scope and potential limitations of these results.

Table 1: Summary statistics

	1963 - 1991		1992 - 2017		Mean
Variable	Mean	Std. Dev.	Mean	Std. Dev.	Difference
Stock monthly excess return (%)	0.913	13.768	1.270	16.876	0.357***
Market cap ($ millions, nominal)	392	1,984	2,962	15,783	2,570***
Market cap (2017 dollars)	1,343	7,012	3,684	19,175	2,341***
Book-to-market	1.070	1.039	0.744	1.204	-0.327***
Beta	1.220	0.542	1.178	0.806	-0.042***
Market excess return	0.409	4.593	0.642	4.190	0.234
SMB return	0.266	2.879	0.167	3.272	-0.099
HML return	0.392	2.567	0.301	3.078	-0.091
SMB factor loading	1.029	0.997	0.888	1.015	-0.141***
HML factor loading	0.123	0.949	0.095	1.150	-0.029***
# stocks per month	2,140	805	2,816	560	676***

Table 2: Summary statistics for 25 portfolios sorted by characteristics and factor loadings

Panel A: July 1963 - December 1991 (N=342 months)						Panel B: January 1992 - June 2017 (N=306 months)				
	Mean monthly excess return:					Mean monthly excess return:				
	Book-to-market quintile					Book-to-market quintile				
Size quintile	Low	2	3	4	High	Low	2	3	4	High
Small	0.31	0.67*	0.72**	0.89***	1.01***	0.21	0.92**	0.87***	1.15***	1.20***
2	0.39	0.66*	0.84***	0.92***	0.99***	0.61	0.87***	0.91***	0.94***	0.98***
3	0.42	0.71**	0.64**	0.85***	0.93***	0.59	0.89***	0.89***	0.92***	1.13***
4	0.46	0.37	0.62**	0.79***	0.88***	0.78**	0.88***	0.79***	0.95***	0.78**
Big	0.37	0.34	0.34	0.52**	0.52**	0.61**	0.74***	0.77***	0.47*	0.83**
	Mean monthly excess return:					Mean monthly excess return:				
SMB factor	HML factor loading quintile					HML factor loading quintile				
loading quintile	1	2	3	4	5	1	2	3	4	5
5	0.38	0.88*	0.90**	0.51	0.52	0.65	1.03**	0.89*	0.68	0.90**
4	0.37	0.67*	0.89**	0.47	0.56	1.03*	0.84**	0.79*	1.13***	0.88**
3	0.61	0.55	0.57*	0.61*	0.60*	0.73*	0.72*	1.10***	0.88***	0.90**
2	0.47	0.54*	0.48*	0.43	0.90***	0.89**	0.61**	0.80***	1.04***	1.09***
1	0.11	0.36	0.38	0.52**	0.48	0.78**	0.42*	0.74***	0.74***	0.77**

Table 3: Risk premium estimates for the Fama French 3-factor model using individual stocks

Parameter	1963-1991	1992-2017	Full Sample
Intercept	0.767***	1.302***	0.997***
	(4.11)	(7.14)	(7.97)
Market beta	-0.268	-0.322	-0.268*
	(-1.50)	(-1.14)	(-1.74)
s (SMB factor loading)	0.276	-0.010	0.135
	(1.45)	(-0.04)	(0.91)
h (HML factor loading)	0.507***	0.368	0.398***
	(2.85)	(1.59)	(2.91)
Average R-squared	2.94%	3.07%	3.17%
Average # observations	2,145	2,846	2,307

Table 4: Risk premium estimates for the characteristics-based model using individual stocks

Parameter	1963-1991	1992-2017	Full Sample
Intercept	1.221***	1.568***	1.374***
	(3.52)	(4.8)	(6.04)
Market beta	-0.144	0.107	-0.036
	(-0.71)	(0.31)	(-0.19)
LN(Size)	-0.114**	-0.135***	-0.120***
	(-2.33)	(-2.73)	(-3.61)
Book-to-market	0.153***	0.150***	0.144***
	(3.03)	(3.57)	(4.43)
Average R-squared	3.87%	3.08%	3.62%
Average # observations	2,136	2,830	2,296

Table 5: Risk premium estimates for the 3-factor model with deciles as explanatory variables

Parameter	1963-1991	1992-2017	Full Sample
Intercept	0.693***	1.492***	1.044***
	(3.66)	(6.87)	(7.54)
Market beta	-0.465**	-0.585**	-0.476***
	(-2.36)	(-2.01)	(-2.93)
SMB factor loading decile	0.077***	0.050*	0.059***
	(2.72)	(1.79)	(3.18)
HML factor loading decil	0.039**	0.005	0.021
	(2.57)	(0.15)	(1.27)
Average R-squared	3.19%	2.37%	3.01%
Average # observations	2,145	2,846	2,307

Table 6: Risk premium estimates for the characteristics-based model with deciles as explanatory variables

Parameter	1963-1991	1992-2017	Full Sample
Intercept	1.080***	1.007***	1.058***
	(3.02)	(2.98)	(4.58)
Market beta	-0.161	0.165	-0.009
	(-0.82)	(0.52)	(-0.05)
Size decile	-0.078**	-0.096**	-0.083***
	(-2.53)	(-2.53)	(-3.74)
Book-to-market decile	0.059***	0.080***	0.065***
	(3.5)	(3.77)	(5.02)
Average R-squared	3.87%	3.26%	3.75%
Average # observations	2,451	3,216	2,556

Table 7: Risk premium estimates for 100 portfolios sorted by size and book-to-market

Parameter	1963-1991	1992-2017	Full Sample
Intercept	0.585***	1.187***	0.869***
	(2.64)	(5.55)	(5.62)
Market beta	-0.143	-0.447**	-0.286**
	(-0.76)	(-2.05)	(-2.01)
s (SMB factor loading)	0.217	0.069	0.147
	(1.52)	(0.4)	(1.34)
h (HML factor loading)	0.321**	0.148	0.239**
	(2.56)	(0.9)	(2.36)
Average R-squared	23.69%	22.96%	23.35%
# observations per regres:	100	100	100

Table 8: Risk premium estimates for 100 portfolios sorted by factor loadings

Parameter	1963-1991	1992-2017	Full Sample
Intercept	0.955	6.575***	3.609***
	(1.37)	(6.02)	(5.62)
Market beta	0.149	0.354*	0.246*
	(0.68)	(1.88)	(1.68)
LN(Size)	-0.269**	-1.325***	-0.768***
	(-2.24)	(-6.38)	(-6.49)
Book-to-market	0.897***	-0.019	0.464**
	(3.59)	(-0.05)	(2.25)
Average R-squared	11.64%	9.11%	10.45%
# observations per regres:	100	100	100

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Who are robo-advisor users?

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Abstract

The purpose of this study is to explore the demand for robo-advising services by analyzing the participants' behavioral characteristics and investment patterns. With the 2015 Financial Industry Regulatory Authority Investor data, we found that robo-advisor users were younger investors with high risk tolerance, whose self-assessment of financial knowledge is comparatively higher than their actual knowledge, and were independent decision-makers. By controlling for those behavioral attributes of robo-advisor users, we also found that robo-advisor users were reluctant to invest in individual stocks, while they showed the largest preference for investing in pooled investment products such as Exchange Traded Funds. Implications of this study's findings can be beneficial to financial planning practitioners, academics, and regulators.

I. Introduction

Robo-Advisors are automated portfolio allocation platforms, many of which apply algorithms based on machine learning. Recent studies suggest an increasing demand for robo-advisory services (Jung, Dorner, Glaser, & Morana, 2018). According to Agarwal, Driscoll, Gabaix, and Laibson (2009), younger investors lack investment knowledge, and many older investors suffer from diminishing cognitive ability. These two groups can benefit most from accessing the services through a low-cost automated investment platform (Fisch, Labouré, and Turner, 2018). Recent reports about the increasing demand for Turnkey Asset Management Programs (TAMP) among financial advisors show that digital integration of technology and the utilization of automated investment platforms are continuing to increase. According to Neal (2019), a Turnkey Asset Management Program (TAMP) is a fee-account technology platform where financial advisors can monitor their clients' investment account. Based on this platform, TAMP programs provide a free digital marketplace where advisors can model their investment strategies. Such a phenomenon shows that the financial advisory industry is entering a new paradigm of reduced transaction costs. While electronic platforms such as TAMPs are not designed to actively let advisors engage in investment activities, many of these platforms make available technology-based tools that facilitate record-keeping and interaction between financial advisors and clients. In other words, it reduces the transaction cost between the financial advisor and its clients that provide technology, investment research, portfolio management, and other outsourcing services for financial advisors.

However, consumers have been slow in warming up to the idea of having their retirement portfolios managed by automated platforms. One recent research on robo-advisors among European investors has shown that 49 percent of the respondents would not utilize a robo platform's service without in-person support from a trained financial advisor (Nicoletti, 2017). In this study, Nicoletti (2017) found that only about 11 percent of the respondents would use a robo-platform instead of accessing a human financial advisor's services. Other factors, such as risk

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tolerance, financial knowledge, and confidence, have been associated with individuals' investment planning decisions (Lusardi & Mitchell, 2008; Wang, 2009). Other recent studies on the demand for robo-advisors have shown that people who used the services of robo-advisors were younger, had higher risk tolerance, and were time-constrained (Fan & Chatterjee, 2020).

This study aims to add to the literature on the demand for robo-advisor platforms by examining whether financial confidence or subjective financial knowledge is associated with the utilization of robo-advisory services. Additionally, this paper investigates the determinants of investment asset selection among those who utilized the services of robo-advisors.

II. Literature review

Current state of robo-advising

Robo-Advisors, or in other words, automated financial advisors, are online platforms that provide investment advice driven by algorithms (Ji, 2017) and machine learning techniques. These investment platforms have emerged as alternative investments compared to traditional human financial advisors. Robo-Advisors have now been around for some time, and their adoption rate has steadily increased over the past decade (Perrin & Duggan, 2015). Indeed, technology has been increasing cost and price efficiencies in the investment arena over the past two decades. For example, a seminal study by Brown and Goolsbee (2000) has found that the internet's democratization reduced the search cost in choosing insurance contracts.

Over the past decade, the financial services market has seen the emergence of robo-advisors or automated investment platforms that provide portfolio management and investment advice to private consumers (Ji, 2017; Woodyard & Grable, 2018). As a low-cost alternative to the traditional financial advisor, robo-advisors provide financial advice by utilizing algorithms programmed to optimize consumers' investment decisions (Ji, 2017; Day, Cheng, & Li, 2018; Kobets, Yatsenko, Mazur & Zubrii, 2018). Robo-Advisory platforms are used by investors and institutions, including financial advisors, investors working with financial advisors, and investors who choose not to work with financial advisors (Financial Industry Regulatory Authority Report (FINRA), 2016). Robo-Advisors help consumers make financial decisions, such as evaluating risk-measurement, selecting portfolios, and rebalancing portfolios.

Recent studies suggest that as technology advances in the long-term, robo-advisors may provide a comparable or a supplementary option to human financial advisors making them increasingly acceptable in the financial services industry (Jung, Glaser, & Köpplin, 2019). Despite the innovation of robo-advisors, consumers' lack of trust has delayed the adoption of robo-advisor solutions by the market (Cheng et al., 2019). One criticism of robo-advisors is that they are designed to only recommend suitable products to consumers (Baker & Dellaert, 2017b). Moreover, although robo-advisors are based on sophisticated algorithmic and machine learning-based frameworks, the capability, integrity, and financial fitness of robo-advisor based services cannot easily be identified and implemented (Baker & Dellaert, 2017b). Research shows that strong customer support and product branding are critical elements of building trust for robo-advisors (Salo, 2017).

Regarding the adoption of robo-advisors, Hohenberger, Lee, and Coughlin (2018) found that subjective assessment of the degree of prior financial experiences can explain the adoption of robo-advisors. Thus, the willingness or motivation to adopt a robo-advisor is positively correlated with previous experiences. People who had more financial transactions in the past were more likely to adopt a robo-advisory system. Regarding the population of robo-advisor users, Woodyard and Grable (2018) found that users of robo-advisors tend to be younger, confident in their financial ability, and distrustful of traditional financial channels.

The market for robo-advising has experienced rapid expansion over the past five years. According to Mercadante (2020), there are several ways robo-advisors facilitate a change in the investment industry. The first change that robo-advisors are facilitating comes from the prevalence of information about financial investments and products. The availability of abundant financial information on the web has made many individual investors feel more empowered to make investment decisions by themselves (with robo-advisors serving as facilitators). The second change is related to the lower barrier into the investment world. Falling transaction costs have created greater access for small investors to invest in the financial markets. While these two aspects are mostly related to the industry's general trend, the primary contribution of robo-advising comes from its ability to rebalance a portfolio and the democratization of quality investments for small investors. Due to wider access to investment advisors through a robo-advising platform (e.g., TAMP), now customers have more real-time access to valuable information. Regarding the current state of the robo-advising industry, according to the Corporate Finance Institute (Corporate Finance Institute (CFI), 2020), the five largest robo-advisors currently operating in the market are Betterment, Charles Schwab, TD Ameritrade (recently bought over by Charles Schwab), the Vanguard group, and Wealthfront. Neal (2019) provides a list of current TAMP providers in Table 1, and as shown, most of the services and products do not differ much from each other, and most of them have the same or similar custodians.

According to Royal (2020), the cost of using robo-advisors includes management fees and the fund’s expense ratios. While the management fees range from 0.25 to 0.5 percent, the funds’ expense ratios to which the robo-advisors allocate investor portfolios may range from 0.05 to 0.65 percent. According to this author (Royal, 2020), robo-advisors have highly sophisticated programmed algorithms and let one manage and monitor individual investors’ portfolios in real-time by providing those small investors with reasonable value propositions.

During the 2020 pandemic, Hicks (2020) finds that stock market volatility and market uncertainty have accelerated the adoption of robo-advisors: the five largest robo-advisors saw a growth of 38% during the first half of 2020 compared with the previous year. The range of investment strategies offered by robo-advisors also expanded during this period. The ten best advisors listed in Hicks’ (2020) study ranged from robo-advisory platforms that used strategies similar to hedge funds to robo-advisors that focused on socially responsible investments (SRI), whereby several of them integrated artificial intelligence (AI) and machine learning-based algorithms in their portfolio management models. Here, the portfolio management styles among the robo-advisors ranged from passive buy and hold strategies to sophisticated active portfolio management strategies.

Table 1. List of current TAMP providers

Firm	Custodian	Total Assets ($M)	Fee Structure	Currently offered programs
Envestnet	Fidelity, First Clearing, Pershing Advisor Solutions, Raymond James Investment Advisor Division, RBC, Schwab Advisor Services, TD Ameritrade Institutional, other	$3,300,000	Asset-based fee	ETF wraps, mutual fund wraps, SMAs, UMAs, UMHs
Independent Advisor Solution by SEI	SEI	$67,215	Asset-based fee (0.29% - 1.23%)	ETF wraps, mutual fund wraps, SMAs, UMAs, UMHs
Assetmark Financial Holdings Inc.	AssetMark, Fidelity, Pershing Advisor Solutions, TD Ameritrade Institutional	$56,700	Other	ETF wraps, mutual fund wraps, SMAs, UMAs, UMHs
Loring Ward & Bam Advisor Services	Fidelity, Pershing Advisor Solutions, Schwab Advisor Services, TD Ameritrade Institutional	$34,000	Asset-based fee (0.10% - 0.65%)	ETF wraps, mutual fund wraps, SMAs, UMAs, UMHs
Brinker Capital	Fidelity, Schwab Advisor Services	$23,782	Asset-based fee (0.00% - 0.64%)	ETF wraps, mutual fund wraps, SMAs, UMAs
Orion Portfolio Solutions	TD Ameritrade Institutional	$15,627	Asset-based fee (0.00% - 0.75%)	ETF wraps, mutual fund wraps, SMAs, UMAs
Sawtooth Solutions	Fidelity, Pershing Advisor Solutions, Schwab Advisor Services, TF Ameritrade Institutional	$11,900	Asset-based fee (0.20% - 0.35%)	ETF wraps, mutual fund wraps, SMAs, UMAs, UMHs
Morningstar Investment Services	Fidelity, Pershing Advisor Solutions, Schwab Advisor Services, TD Ameritrade Institutional	$11,200	Asset-based fee (0.05% - 0.55%)	ETF wraps, mutual fund wraps, SMAs, UMAs
Symmetry Partners	Fidelity, Schwab Advisor Services, TD Ameritrade Institutional	$9,400	Asset-based fee (0.15% - 0.50%)	ETF wraps, mutual fund wraps, SMAs, UMAs, UMHs
Frontier Asset Management	Fidelity, LPL Financial, Pershing Advisor Solutions, Schwab Advisor Service, TD Ameritrade Institutional	$4,185	Asset-based fee (0.30% - 0.60%)	SMAs
Advisors Capital Management	Fidelity, LPL Financial, Pershing Advisor Solutions, Schwab Advisor Services, TD Ameritrade Institutional	$2,400	Asset-based fee, Flat fee (0.35% - 0.80%)	SMAs, UMAs
Fusion Capital Management	Schwab Advisor Services, TD Ameritrade Institutional	$1,652	Other (0.05% - 0.45%)	ETF wraps, mutual fund wraps, SMAs, UMAs, UMHs

Axxcess Platform	Fidelity, Schwab Advisor Services, TD Ameritrade Institutional	$1,650	Asset-based fee (0.05% - 0.65%)	SMAs, UMAs, mutual fund wraps
Dunham	Other	$1,500	Asset-based fee (0.25% - 2.25%)	Mutual fund wraps
SmartX Advisory Solutions	Fidelity, Pershing Advisor Solutions, Schwab Advisor Services, TD Ameritrade Institutional	$1,500	Asset-based fee (0.05% - 0.15%)	UMAs, SMAs, UMHs
Lockwood Managed 360	Pershing Advisor Solutions	$1,391	Asset-based fee (0.20% - 0.95%)	ETF wraps, mutual fund wraps, SMAs, UMAs
3D Asset Management	Schwab Advisor Services, TD Ameritrade Institutional	$805	Asset-based fee (0.30% - 0.65%)	ETF wraps, mutual fund wraps, UMAs, SMAs, UMHs

Note. Exchange-traded fund (ETF) wrap accounts, mutual fund accounts, separately managed accounts (SMAs), unified managed accounts (UMAs), unified managed households (UMHs); Reproduced with permission from "Competition among TAMPs heats up: Financial advisors' growing interest in outsourcing is luring new entrants to the Turnkey Asset Management platform space," by Ryan W. Neal, 2019, *Investment News*, September 2-6, p.11. Copyright 2019 by Investment News. The robo-advisors listed in this table are not representing all the products out in the market. The five largest robo-advisor companies are Vanguard, Wealthfront, Charles Schwab, TD Ameritrade, and Betterment (i.e., the custodians). Products and firms listed in Table 1 provide a Turnkey Asset Management Program (TAMP): an interactive robo-advising tool for financial advisors. A TAMP helps financial advisors to reduce the time of due diligence (e.g., investment research and selection, portfolio rebalancing, maximization of tax efficiency). They let the firms in this table (i.e., custodians) build their clients' investment portfolios at an asset-based fee. A TAMP can be an outsourcing tool, but it is also a streamlined platform where the financial advisor can monitor a client's account and make suggestions. Since a financial planner or advisor is restricted to advising only, a TAMP platform improves communication by providing better and faster information to the clients, whereby the clients make the ultimate decision of investments. Most of those services charge an asset-based fee, and the types of products are listed in the last column.

Issues revolving around robo-advising

Robo-Advisors face system-wide scaling issues such as not addressing specific individual investor concerns (Baker & Dellaert, 2017b). The challenge of providing individualized solutions for financial advisement may hinder the widespread use of robo-advisors as an overall effective solution. In other words, robo-advisors are missing the qualities that human advisors possess may be a determining factor in consumer acceptance of robo-advisors versus their human alternatives (Faloon & Scherer, 2017).

However, other studies indicate that robo-advisors have the potential to become the preferred investment advisory solution for regular clients and high-net-worth clients alike (Uhl & Rohner, 2018). Offering a low-cost advisory solution, robo-advisors have appealed to young, technologically knowledgeable consumers who are averse to utilizing traditional channels of financial advice provided by human advisors (Woodyard & Grable, 2018).

A recent study suggested a consumer's willingness to engage with a robo-advisor solution depends significantly on its usability (Jung, Dorner, Weinhardt, & Pusmaz, 2018). Consumers report experiencing a range of emotions when using robo-advisors (Hohenberger, Lee, & Coughlin, 2018). For example, one study indicated that consumer experience positive emotions such as joy when using robo-advisors. Conversely, negative responses of anxiety can diminish interest in the use of robo-advisors (Hohenberger, Lee, & Coughlin, 2019). Investors may be more likely to follow the advice of a robo-advisor when the advisor exhibits fewer human characteristics. Many investors also decreased their use of robo-advisors when robo-advisor managed portfolios underperformed other investment opportunities over the short term (Hodge, Mendoza, & Sinha, 2020).

The emergence of new technology such as Artificial Intelligence (AI) can make robo-advisors provide even more cost-effective portfolio management solutions for investors (Lee, Kwon, & Lim, 2017). One example of AI implementation is the ability to recreate human decision-making in a robo-advisory solution with the help of self-learning AI algorithms (Tokic, 2018). Robo-Advisor solutions are typically based on the lack of human interactions in hopes consumers will comprehend and retain the information given without the need to ask questions (Salo, & Haapio, 2017). The use of technology to improve financial advisement is not without concerns from industry and consumers.

The introduction of robo-advisors technology to the financial industry has unmasked legal and policy limitations in providing automated advisory services to the financial sector. Investment Advisors Act of 1940 was designed with a human interaction behavior focus. It is argued that robo-advisors are incapable of providing a comparable amount of care a human advisor offers to meet the Advisers Act's standards (Ji, 2017). In a FINRA report, human investment advisers are deemed fiduciaries under the Investment Advisors Act of 1940 (FINRA, 2016). The financial advisor's fiduciary responsibility requires the adviser to provide investment advice in the client's best interest. According to the FINRA report, one way to integrate the portfolio management solutions that robo-advisors provide would be to make these available to clients as a deliverable by a human financial advisor who can play the primary fiduciary function (FINRA, 2016). Robo-Advisors' services do not fill the standard of a fiduciary. Therefore, studies have suggested not to hold robo-advisors to the same regulatory standard that human advisors are subject to (Baker & Dellaert, 2017a).

Despite this efficient system of robo-advising, a question continues to remain in academia: How reliable and consistent is a robo-advisor or an automated investment platform? And what are consumers' perceptions of using a robo-advisor? Pertinent to the first question, Ciccotello and Wood (2001) conducted a real-life simulation based on three types of investors and found that robo-advisors are doing an excellent job recommending financial products. Ciccotello and Wood's (2001) argument is that automated investment platforms have a more consistent recommendation than real-life advisors in certain product types. Such an observation might come from the fact that robo-advisors are run based on a mathematic algorithm that predicts the same output when the input data is similar. The only difference in the outcome by different platforms came from different assumptions and methods used by the robo-advisor. By measuring the coefficient of variation of the output of different robo-advisors, the authors (Ciccotello & Wood, 2001) found that all robo-advisor brands had similar outputs in terms of Roth conversions or life insurance products rather than in investment portfolio related results, while asset allocation or estate tax estimations were better performed with real-life financial advisors. Regarding portfolio allocation, contrary to the pundits' expectations, robo-advisors had difficulties in predicting a consistent output for clients with a complex composition of assets and wealth. Instead, real-life advisors tend to project a more consistent asset allocation strategy than robo-advisors, even though a human financial advisor might exhibit inconsistent investment strategies and philosophies. Additionally, Belanche, Ariño, and Flavian (2019) found that individual investors, who had a deeper understanding of information technology and robots, were more likely to trust and utilize rob-advisors' services. The authors (Belanche, Ariño, & Flavian, 2019) also found that attitudes towards robo-advisors and the utilization of these services varied by the investors' socio-economic and individual characteristics.

III. Empirical analysis

The estimation strategy of this paper was based on a two-phase analysis of robo-advisor users. The first part is an analysis based on the characteristics of those users (see Table 3). In this phase, we found distinctive behavioral patterns of investors who use automated advisory systems (i.e., robo-advisors). This was done by regressing a binary probability model (i.e., a logit model in this study) of whether one is a robo-advisor user (dependent variable) on the characteristics of an investor (independent variables). These included variables pertinent to demography, risk tolerance, own assessment of financial knowledge, financial literacy score, and investment style. Based on the regression results, we determined the characteristics of robo-advisor users by identifying statistically significant variables.

In the second phase of our empirical analysis, we ran another logit model. The dependent variables were financial products invested by the survey respondent in the Financial Industry Regulatory Authority (FINRA) survey (see Table 4). Each financial product was then regressed on whether one is a robo-advisor user, the respondent's risk tolerance level, own assessment of financial knowledge, financial literacy score, and investment style. Except for excluding the demography variables and instead including the robo-advisor variable (which previously was the dependent variable in the first model), the rest of the variables were practically the same as in the previous model: they were used as control variables (i.e., the model in Table 3).

FINRA investor data and variables

As mentioned before, this study uses the Financial Industry Regulatory Authority (FINRA) National Financial Capability Study (NFCS) dataset. This study uses the 2015 wave of the NFCS (state-by-state version) and the merged 2015 FINRA Investors' data. The merged dataset includes information about participants: Their socio-demographic characteristics, invested financial products, risk-tolerance level of investors, investment styles, own assessment of financial knowledge, financial literacy, and whether one uses an automated financial advisor (i.e., robo-advisor). The entire sample size of our investment data contained 2,000 observations, while all the questions used in this study were questions asked in a binary fashion. Additionally, we controlled for the respondents' state of residence, which was later used for State-based fixed effects to subdue different State legislatures affecting investments and different internet infrastructures.

Again, it is emphasized that only the 2015 version had the pertinent question regarding the use of automated advisors. Unfortunately, the most recent FINRA survey dropped question C11, so that the 2015 version is the 'only' survey that has a question regarding the use of robo-advisors. As for challenges that might argue that the data set used in this study is a little outdated, we argue that our study bases on the behavioral attributes of robo-advisor users. In other words, our study is exploring the fundamental characteristics of certain types of investors and, based on their attributes, how they invest. Thus, unless the investors' behavioral characteristics investing in a certain financial product change, or unless there is a financial product that is different from the conventional products in the market, our argument firmly stands with the notion that the patterns of investments would not change because investors' characteristics do not change easily.

Table 2. Summary statistics

VARIABLES	(1) Obs.	(2) Mean	(3) Median	(4) St. Dev.	(5) Min	(6) Max
Financial products						
STOCK	2,000	0.748 (74.8%)	1	0.435	0	1
BOND	2,000	0.347 (34.7%)	0	0.476	0	1
MFUND	2,000	0.665 (66.5%)	1	0.472	0	1
ETF	2,000	0.221 (22.1%)	0	0.415	0	1
ANNU	2,000	0.326 (32.6%)	0	0.469	0	1
WLIFE	2,000	0.416 (41.6%)	0	0.493	0	1
CMMFTRE	2,000	0.112 (11.2%)	0	0.315	0	1
OTHER	2,000	0.147 (14.7%)	0	0.354	0	1
Risk Tolerance						
Substantial risk	2,000	0.0985 (9.85%)	0	0.298	0	1
Above avg. risk	2,000	0.294 (29.4%)	0	0.456	0	1
Avg. risk	2,000	0.498 (49.8%)	0	0.500	0	1
Investment style						
Own decision	2,000	0.407 (40.7%)	0	0.491	0	1
Variable of interest						
Robo-Advisor	2,000	0.129 (12.9%)	0	0.335	0	1
Own finance assessment						
Very high	2,000	0.117 (11.7%)	0	0.321	0	1
Fees						

Fixed fee	2,000	0.316 (31.6%)	0	0.465	0	1
Controls						
Gender (Male)	2,000	0.550 (55.0%)	1	0.498	0	1
Age (35-54)	2,000	0.316 (31.6%)	0	0.465	0	1
Age (55+)	2,000	0.522 (52.2%)	1	0.500	0	1
Ethnicity (White)	2,000	0.803 (80.3%)	1	0.398	0	1
Education (College)	2,000	0.610 (61.0%)	1	0.488	0	1
Income (50K-100K)	2,000	0.447 (44.7%)	0	0.497	0	1
Income (100K+)	2,000	0.344 (34.4%)	0	0.475	0	1
Financial literacy						
State + Investment data	2,000	8.905	9	3.260	0	16

Note. The total number of observations in the 2015 FINRA investor dataset was 2,000. The percentages in the parentheses only apply to binary variables.

More than half of the respondents answered that they would hire a financial advisor because they want to avoid loss (64.7%) and improve performance (67.5%). Others answered that they would like to improve their portfolio performance (51.6%) or access to investment opportunities (44.3%) that they would not have had without a financial advisor.

Regarding financial knowledge, ten questions were asked in the investor data and six in the primary state-by-state population data. The original survey used the same financial literacy questions of Lusardi and Mitchell's work (2014) and asked those questions to the survey respondents. In this sense, they are 'not' the same survey respondents as in the original study conducted by Lusardi and Mitchell (2014). By putting together Lusardi and Mitchell's financial literacy metrics (2014) and the FINRA financial literacy questions (that were asked to all the survey respondents in the 2015 FINRA survey, we created a comprehensive financial literacy score that incorporated survey questions originated from both. Based on these two measurements, we gave each right question one point so that the maximum achievable financial literacy score was 16. The average was 8.91 points, close to the mean of 8 points, and the standard variation was 3.26 points. Contrary to the well-distributed financial literacy scores, only a few people in the survey answered that they have a very high finance knowledge level. Only 11.7% of the respondents self-assessed themselves as having a very high knowledge base, which indicated that many respondents lacked confidence and faith in their knowledge base.

In terms of investment style, 40.7 percent answered that they make their own decisions, and 41.1 percent responded that they seek professional advice. In terms of the fee structure, 31.6% were paying a fixed monthly or annual fee. Other than the variable related to the usage of robo-advisors, major variables that were used as dependent variables in this study were related to investment choices. The FINRA investor data asked respondents about what type of financial product one is currently owning. Out of 2,000 observations, on average, 74.8 percent owned stocks (STOCK), followed by 66.5 percent of respondents who owned mutual funds (MFUND). Bonds (BOND) were owned on average by 34.7 percent, annuities (ANNU) by 32.6 percent, exchange-traded funds (ETF) by 22.1 percent, commodities and futures (CMMFTRE) by 11.2 percent, and other investment products such as real estate investment trusts (REITs), options, private placements, or structured notes (OTHER) were owned by 14.7 percent.

The gender composition included 55 percent of males and 45 percent of females regarding the demographic control variables. Also, almost half of the respondents were over 55 years old (52.2%), and 80.3 percent were racially white. The education level of investors showed that, on average, 61 percent were college-educated. The composition of income levels included 44.7 percent of people who earned between \$50,000 and \$100,000, while around 34.4 percent earned over \$100,000.

Table 3. Robo-Advisor regression

VARIABLES	(1) ROBO	(2) ROBO	(3) ROBO	(4) ROBO
Controls				
Gender (Male)	-0.142	-0.114	0.100	0.0893
	(0.172)	(0.165)	(0.182)	(0.183)
Age (35-54)	-0.853***	-0.820***	-0.702***	-0.713***
	(0.190)	(0.209)	(0.213)	(0.213)
Age (55+)	-1.809***	-1.713***	-1.428***	-1.408***
	(0.268)	(0.272)	(0.274)	(0.274)
Ethnicity (White)	-0.392**	-0.319*	-0.225	-0.217
	(0.192)	(0.192)	(0.198)	(0.202)
Education (College)	-0.190	-0.0740	0.110	0.123
	(0.164)	(0.163)	(0.180)	(0.180)
Income (50K-100K)	-0.298	-0.262	-0.202	-0.192
	(0.238)	(0.223)	(0.234)	(0.234)
Income (100K+)	-0.682***	-0.715***	-0.515**	-0.486*
	(0.223)	(0.237)	(0.248)	(0.251)
Risk Tolerance				
Substantial risk	3.912***	3.217***	3.483***	3.420***
	(0.548)	(0.507)	(0.501)	(0.503)
Above avg. risk	2.513***	2.215***	2.568***	2.574***
	(0.546)	(0.537)	(0.534)	(0.530)
Avg. risk	1.565***	1.454**	1.739***	1.741***
	(0.555)	(0.575)	(0.575)	(0.573)
Own finance assessment				
Very high		1.554***	1.481***	1.437***
		(0.269)	(0.278)	(0.272)
Financial literacy				
State + Invest data			-0.153***	-0.156***
			(0.0292)	(0.0292)
Investment style				
Own decision				0.274*
				(0.142)
Constant	-3.678***	-3.968***	-3.457***	-3.470***
	(0.829)	(0.779)	(0.783)	(0.792)
Observations	2,000	2,000	2,000	2,000
State Fixed Effect	applied	applied	applied	applied
Pseudo *R*-Squared	0.299	0.339	0.356	0.357

Note. The dependent variable ROBO is a binary variable on a question in the 2015 FINRA investor survey:

question C11 (36th question). This question asked in a dichotomous fashion, “Have you ever used an automated financial advisor that provides investment advice and makes trades on your behalf?” This binary variable was then used as the dependent variable in all four models in this table. The robust standard errors are in parentheses. The model was based on a Logit model where the error terms were clustered by States. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Profile of robo-advisor users

The first analysis was conducted based on a logit regression where the dependent variable was a binary variable of whether one was using an automated financial advisor (i.e., robo-advisor). The results are reported in Table 3, and State fixed effects were applied to exclude idiosyncratic attributes by States, such as the degree of internet service provided and its dissemination among residents of each State or different State legislatures that might affect one’s investment. The results in Table 3 are reported in log-odds. In terms of the control variables' significance, all age groups and the income group earning over $100,000 per year showed a significant and negative sign. In this study, the age groups of 35 to 54 and the age group over 55 years were negatively associated with the utilization of a robo-advisor compared to the lowest age group of 18 to 34 (i.e., the reference group). In a similar context, people with income over $100,000 were less likely to make their investment decisions based on this electronic platform than people who earn less than $50,000 (i.e., the reference group). These results suggest that people older in age are reluctant to rely on the services of an automated investment platform, and people with higher income were also negatively associated with the use of robo-advisors.

The risk tolerance variables were compared to the reference group of highly risk-averse individuals (i.e., individuals who would take ‘no risk:’ highly risk-averse group). In all risk-tolerance levels, survey respondents showed a significant and positive association towards using a robo-advisor. This is an indicator that the use of this electronic platform is highly correlated with taking risks. In all four models, substantial risk-takers had the largest coefficient, followed by above-average risk-takers and average risk-takers. Here, all variables were compared to the risk-averse investor who served as a baseline comparison group.

The financial literacy variables consistently showed a significant negative effect throughout Models 3 and 4. As elaborated before, the financial literacy variable was constructed by incorporating financial literacy test scores from both the State-by-State and Investor data, which ranged from zero to 16 points maximum. Each question was graded by one point if the respondent got the question right. A negative sign alerts that respondents with a low level of financial knowledge have a higher propensity towards using a robo-advisor. Pertinent to this result, the result of the investment style (i.e., “own decision”) indicates that robo-advisor users are independent because they prefer to make their own financial decisions rather than rely on acquaintances or third-party advisors.

The paradox of robo-advisor users regarding their actual knowledge and self-assessment can be observed by two opposite significant financial literacy results and one’s financial knowledge assessment. The positively significant result of one’s own financial assessment indicates that the robo-advisor users tend to have high confidence in their knowledge. This is further supported by the investment style variable, where investors who make their financial decisions on their own have a strong inclination to be a robo-advisor user.

Table 4. Investment patterns

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	STOCK	BOND	MFUND	ETF	ANNU	WLIFE	CMMFTRE	OTHER
Variable of Interest								
Robo-Advisor	-0.142	0.689***	0.943***	1.093***	0.835***	0.378*	0.985***	1.017***
	(0.222)	(0.168)	(0.268)	(0.237)	(0.178)	(0.203)	(0.232)	(0.188)
Risk Tolerance								
Substantial risk	0.821***	0.294	0.371	2.088***	0.0276	0.193	1.815***	0.615*
	(0.275)	(0.230)	(0.266)	(0.466)	(0.252)	(0.246)	(0.367)	(0.361)
Above avg. risk	1.143***	0.298	0.855***	1.756***	-0.190	0.231	1.735***	0.710**
	(0.208)	(0.194)	(0.194)	(0.448)	(0.193)	(0.160)	(0.400)	(0.297)
Avg. risk	0.603***	0.191	0.734***	1.541***	-0.0145	-0.0420	0.802*	0.460
	(0.179)	(0.184)	(0.220)	(0.441)	(0.190)	(0.156)	(0.427)	(0.283)
Own finance assessment								
Very high	0.493**	0.834***	0.223	0.814***	0.279	0.398**	0.684***	0.794***
	(0.203)	(0.169)	(0.231)	(0.196)	(0.193)	(0.180)	(0.244)	(0.196)
Financial literacy								
State + Invest data	0.0432**	-0.0171	0.109***	0.0660***	-0.0459***	-0.0567***	-0.0632**	0.0852***
	(0.0208)	(0.0166)	(0.0160)	(0.0197)	(0.0153)	(0.0182)	(0.0274)	(0.0286)
Investment style								
Own decision	0.303**	-0.544***	-0.917***	-0.0141	-0.764***	-0.327***	0.0646	0.410***
	(0.153)	(0.133)	(0.106)	(0.124)	(0.104)	(0.123)	(0.210)	(0.147)
Fees								
Fixed fee	-0.259*	0.433***	0.401***	0.243**	0.535***	0.636***	0.497**	-0.0410
	(0.145)	(0.107)	(0.132)	(0.118)	(0.121)	(0.110)	(0.213)	(0.163)
Constant	-0.120	-0.971***	-0.836***	-3.748***	-0.323	-0.362	-3.527***	-3.434***
	(0.229)	(0.207)	(0.245)	(0.456)	(0.223)	(0.650)	(0.603)	(1.123)
Observations	2,000	2,000	2,000	2,000	2,000	2,000	2,000	2,000
State Fixed Effect	applied	applied	applied	applied	applied	applied	applied	applied
Pseudo *R*-Squared	0.0593	0.0899	0.0957	0.148	0.0882	0.0703	0.205	0.109

Note. The dependent variables are all binary variables that asked the survey respondent whether the respondent was investing in one of the financial products: STOCK (individual stocks), BOND (individual bonds), MFUND (mutual funds), ETF (exchange-traded funds), ANNU (annuities),

CMMFTRE (commodities or futures, or OTHER (REITs, options, private placements, or structured notes). The robust standard errors in parentheses, whereby the error terms were clustered at the State level.
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Investment patterns of robo-advisor users

In order to investigate the investment patterns of robo-advisor users after controlling for other socio-demographic, risk, and financial capability related factors, we ran a logit model based on financial products as dependent variables. The reason for applying a State-based fixed effect was because we wanted to control for dissimilar internet distributions and different State legislatures that might affect one's investment behavior. The dependent variables included in the model of Table 4 were questions regarding one's investment portfolio. They asked whether the respondent was investing in individual stocks (STOCK), individual bonds (BOND), mutual funds (MFUND), exchange-traded funds (ETF), annuities (ANNU), whole life insurance (WLIFE), commodities or futures (CMMFTRE), or other investments such as REITs, options, private placements, and structured notes (OTHER). All were binary variables that correspond to the value of one if one has an investment in one of the investment products above. In Table 4, the variable of interest is the question in the FINRA dataset that asks whether one has ever used an automated financial advisor. Pertinent to this variable, the results in Table 4 show positive and significant results in all product types except individual stocks (Model 1). Regarding the magnitude of the coefficients, Exchange Traded Funds (ETF) showed the largest coefficient, followed by other products (OTHER: REITs, options, private placements, or structured notes) and commodities and futures (CMMFTRE). This result indicates that there is a preference for robo-advisor users to invest in packaged financial products such as ETFs. However, it is also possible that individual investors who used the services of robo-advisors had a preference for the utilization of ETFs because it was suggested by the vendor or the robo-advisor itself. Whether the vendor directed the investor towards investing in ETFs because this vendor is selling those products cannot be confirmed based on the limited data and pool of variables available in the FINRA dataset. However, whether the investor made a certain choice based on the analysis given by the robo-advisor is possible in the sense that the robo-advisor computes the optimal portfolio allocation and types of products based on the behavioral information saved by the investor. From this aspect, a recommendation by the robo-advisor is a reflection of the investor's own predisposition towards ETFs.

Regarding the control variables, the risk-tolerance variables show that people who invest in financial products are, on average, risk-takers. The association is positive and significant for all products other than insurance-based products such as annuities and whole life insurance products. Similarly, subjective financial knowledge was also significant and positively associated with investing in all types of investment products except annuities. Objective financial literacy was positively associated with investments in stocks, ETFs, mutual funds, and other investment products. Yet, it was negatively associated with investments in annuities, whole life insurance products, and commodities. Respondents who made their own investment decisions were positively associated with investing in stocks and other products but were negatively associated with investing in bonds, mutual funds, annuities, and whole life insurance products. In order to assess whether a fee structure was affecting one's investment decision, we also controlled for fixed fees in our regression model. The results indicated that the preference for fixed fees was negatively associated with investing in stocks but positively associated with investing in bonds, mutual funds, ETFs, annuities, and whole life insurance products.

IV. Discussion

Robo-Advisory systems or automated financial advisors are emerging as an alternative to the traditional human-based financial advisory profession (Ji, 2017). Our study suggests that robo-advisor users have certain socio-demographic characteristics and investment preferences. The robo-advisor users were relatively young, with a greater risk tolerance level, and a high subjective financial literacy. However, robo-advisor users were negatively associated with objective financial literacy. These findings are consistent with the results found in Hohenberger, Lee, and Coughlin's (2018) study. Regarding robo-advisor users' investment patterns, robo-advisor users showed a strong preference for ETFs, commodity and futures, as well as other products such as REITs, options, private placements, or structured notes.
Lee and Shin (2018) submit that technological advancements are the greatest innovations in the financial industry. It is evolving towards higher speed, deregulation, and lower cost. Certainly, the current state of the robo-advisory technology had evolved beyond the state in 2015 when our dataset was created. Yet, we argued that the behavioral characteristics of robo-advisor users are exogenous so that their preferences for certain financial products would not change. We acknowledge that our study was constrained because a more recent wave of the dataset with this information regarding the utilization of robo-advisory platforms was not available in the later wave of the FINRA dataset. However, given the rapid growth, adaptation, and changes taking place in the FinTech industry, and more specifically, in the robo-advisor market, future studies need to examine these associations with more recent datasets.

As for prospects of the robo-advising industry, according to a survey by Charles Schwab (2018), it is expected that nearly 58% of Americans are expected to use robo-advisors by 2025. Around 45% said that robo-advisors will have a big impact on financial services, whereby 71% of the respondents still wanted human access on the platform. This was noticeable among Millennials. Around 80% of the Millennials preferred robo-advisers that also had access to human advisors. While Millennials were the primary users of robo-advisors, nearly 46% of the Baby Boomers could find their needs by using a robo-advising platform, and 45% of them presumed to use one by 2025. This survey result validates our findings in the sense that in our empirical analysis (Table 2), older generations were less likely to use a robo-advising platform as compared to the youngest reference group in our sample.

Regarding the current state of robo-advisor users in the population, about 60% of robo-advisor users in the United States are Millennials, and 25% are Generation X people. Most of them expressed that managing their investment portfolio on a robo-advising platform is easy.

According to a report by KPMG (2015), the leading FinTech start-ups are found in China and the United States, whereby China is amongst the largest markets in the credit market. Indeed, as Diemers, Lamaa, Salamat, and Steffens (2015) reported, the FinTech industry's ecosystem should not ignore the role of the government. That is, the FinTech industry should not only focus on technological advancement but also should incorporate best practices that are consistent with the prevailing policies and regulations.

Personalization is key in the robo-advising industry. Indeed, every investor has a different risk tolerance level and has a different portfolio based on one's preferences. While these two aspects are always present in any environment, the emergence of robo-advisors empowered the investor with more optimization tools to build, rebalance, and monitor one's portfolio by reducing the labor cost to human advisors. According to Allayannis and Becker (2019), such a phenomenon of customization, compressed transaction cost, and availability of data-driven optimization tools are the trends that will continue to drive the growth of robo-advising in the near future.

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Estimating the Cost of Capital for Operating Assets

Timothy Vines and ChengHo Hsieh

Abstract

A firm's total assets include non-operating and operating components. In the conventional value-based management and economic value-added models, the value created comes from the firm's operating assets; therefore, the weighted average cost of capital in the models should also be based on the operating assets instead of the total assets. A method to find this cost of capital is presented. This modification also has implications for other areas in the study of financial management, such as capital budgeting and capital structure.

I: INTRODUCTION

Value Based Management

The 1980's produced many headlines associated with the market for corporate control. Equally important, this decade produced a shift in majority stock ownership from individual shareholders collectively to institutional investors. Corporate managers found that societal concern over agency relationships was increasingly leading to activism by the more sophisticated institutional investors and to changes in the legal environment. The need for managers to cooperate with ownership and find better ways to communicate the relationship between decision making and firm value became increasingly important.

Prior to these changes, ratios based on accounting earnings and discounted cash flow techniques were the most frequently used measures to supplement stock price as managerial performance measures. The reasons for accounting information to deviate from economic valuations are well established.[1] Discounted cash flow techniques are hampered by the need to adjust existing accounting information. Chari (2009) finds that there may be as many as 160 possible adjustments possible in the transformation of earnings into cash flow, although only 7 are frequent and significant.

Determining the best way to measure firm performance and how it is affected by decisions has been a subject of great interest to business social scientists. Of much recent notoriety is the growing literature on value-based management (VBM). The value of the firm's operating assets, V_O, is taken to be the present value of the free cash flow from operation, FCF.

$$V_o = \sum \frac{FCF_t}{(1+WACC)^t} \qquad (1)$$

In this equation, t is the time period from 1 to infinity, and WACC is the weighted average cost of capital of the firm given capital structure. Traditionally WACC is defined as:

$$WACC = W_D R_D (1 - T) + W_S R_S \qquad (2)$$

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[1] See for example, Sloan (1996), Shrieves and Wachowicz (2001), or Martin and Petty (2000).

In this equation, the W's represent the weights of debt (D) and equity (S), R's are the costs to the firm of each type of financing, and T represents the tax rate.

The total market value of the non-operating assets, V_N, is added to V_O to obtain the total value of the firm, V.

$$V = V_O + V_N \tag{3}$$

The market value of debt is then subtracted from the value of the firm to arrive at the estimated value of equity, V_S. The estimated stock price per share is V_S divided by the number of shares outstanding.

The key to VBM seems to be trying to identify how managerial decisions have affected stock value in a way that is not masked by systematic factors in the economy and financial markets or by the nuances of accepted accounting practices. Often this avenue of research is so heavily focused upon the overall measure and its important correlation with observed market value, or on accounting or cash flow data definitions and adjustments, that serious consideration of the appropriate measure of WACC in this context has been somewhat neglected. This is important because without a meaningful way to accurately measure WACC, biases can be introduced into the performance metrics which detract from the desired result of identifying the true link between decisions and performance and to the value of the firm's debt and equity.

Economic Value Added and Market Value Added

Although conceptually compatible with Equation (1) and other discounted cash flow techniques[2], the models most often associated with VBM are known as residual income models. Perhaps the most frequently discussed are Economic Value Added (EVA) and Market Value Added (MVA) by Stewart (1991). EVA is the additional firm value created in a period. MVA is the net value created since the beginning of a company and is also the sum of the present value of all the expected future EVA.

$$EVA = NOPAT - WACC(OC) \tag{4}$$

Alternatively,

$$EVA = (ROIC - WACC)(OC) \tag{5}$$

In these equations, NOPAT is net operating profit after taxes and OC is operating capital (book value of operating assets) considering adjustments for intangibles and sometimes leases. Although precise variable definitions are sometimes vague and differ in various papers discussing the usefulness of EVA, NOPAT is conceptually like FCF. ROIC is the return on invested capital, which is equal to NOPAT/OC. Equations (4) and (5) indicate that EVA is additional operating cash created over and above the operating and financial cash flows.

$$MVA = Market\ Value\ of\ Stock - Book\ Value\ of\ Equity \tag{6}$$

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[2] See for example Dillon and Owers (1997), Hartman (2000), and Shrieves and Wachowitz (2001).

MVA is interpreted as the market's perception of the current value of the expected future EVA. It is the additional market value created by managerial decisions. These measures are complimentary and interdependent. Both rely upon publicly available information that allows users to verify statements about performance issued by the managers of adopting firms. Adjustments to this public information made by the users and by academics studying the phenomenon have been debated by many, but the preponderance of the evidence suggests that EVA and MVA outperform the use of accounting information alone as a determinant of market value.

Alternate versions of EVA have been presented. The predominant motivation for the restatements seems to be variable redefinitions that the corresponding authors feel make significant improvement. Surveys and the literature indicate VBM and EVA are widely adopted by firms world-wide. After the initial wave of publicity and academic interest in the U.S., value-based management techniques spread globally. Ryan and Trahan (1999) and Dodd and Johns (1999) survey usage and attitudes among U.S. firms. Feltham, et.al. (2004) study Canadian firms. Fernandez (2002) investigates the use by Spanish firms. Sandoval (2001) uses data from firms in Chile, while West and Worthington (2004) base their conclusions on Australian firms. Yet, in the thousands of words subsequently written about EVA, very little has been related to the use of WACC. This is again problematic due to the essential role the cost of capital plays in the technique. Using a false measure of capital cost results in inaccurate measures of value, making it much more difficult to establish the important links between decisions and value that is the cornerstone of the study of financial management.

In the following section we explain why the WACC currently used for VBM and EVA is not correct and result in over- or under-valuation. In Section III, we present the correct WACC, the WACC for operating assets, and use a numerical example to show how it is estimated. We also briefly explain how the correct WACC improves capital budgeting process and the determination of optimal capital structure. In Section IV, we apply the findings to clarify and improve the MVA. Section V concludes this paper.

II: THE WACC IN VBM AND EVA

Stewart (1994) makes several clarifying comments about EVA and MVA and how to use them. He has pointed out that there are as many as 164 accounting-based performance measurement issues that could be adjusted for, but an individual firm typically would only need 5 to 10 that have material effect. The only adjustment to WACC specifically mentioned is the inclusion of capitalized operating leases in the weight of debt. Stewart also compares MVA to NPV in use and interpretation. The value created by managers at the firm level is analogous to the value created by a positive NPV project when the expected future project cash flows are discounted with WACC. Herein lies the problem with a mis-specified WACC measure. The market value of the weights of financing in the WACC calculation will add to 100% and by necessity will equal the market value of all the firm's assets. This would include non-operating assets that are held for a variety of beneficial reasons not related directly to operations. Such assets may be held to manipulate the perception of overall firm risk, to satisfy bond or loan covenants, or as financial slack. In other words, although these non-operating assets have liquidation value and market value, they do not directly contribute to the NOPAT or FCF that is capitalized in Equation (1), or to EVA and MVA. Prior to discounting the firm's expected cash flow stream, WACC should be adjusted for the presence of non-operating assets. This would enable analysts and researchers to, in effect, measure the performance of the assets that generate cash flows and other assets separately and more accurately.

Consider the formulation of WACC in Equation (2) as the comprehensive firm WACC, $WACC_{COMP}$. In essence, $WACC_{COMP}$ should be thought of as the combined financial cost of the operating assets, $WACC_{O}$, and the cost of the non-operating assets, $WACC_{N}$.

$$WACC_{COMP} = \frac{O}{A}(WACC_{O}) + \frac{N}{A}(WACC_{N}) \qquad (7)$$

In this equation, O is the size of the operating assets, A of the total assets, and N of the non-operating assets.

Normally, non-operating assets, held for financial flexibility or liquidity, tend to offer lower rates of return than operating assets. Thus, one would expect that $WACC_{N}$ is lower than $WACC_{O}$, although this does not have to be the case. If this is the case, using $WACC_{COMP}$ would result in overvaluation in both EVA and VBM. Similar arguments can be made when $WACC_{COMP}$ is used in capital budgeting as the discount rate for NPV or the hurdle rate for IRR. The literature posits that if the risk level of a project under consideration is close to the average of the firm's existing assets, $WACC_{COMP}$ can be used as the discount rate to calculate the project's NPV or as the hurdle rate for the project's IRR. However, this is correct only if the "existing assets" include all assets. In the case that "existing assets" include only operating assets, one should use $WACC_{O}$, instead of $WACC_{COMP}$ for both NPV and IRR.

In the rare case that the non-operating assets are riskier than the operating ones, like minority interest investments in firms with greater risk, the opposite effect would occur. Using $WACC_{COMP}$ rather than $WACC_{O}$ would result in undervaluation.

III: ESTIMATING THE WACC FOR OPERATING ASSETS

To illustrate the benefit of this new way to think about the cost of capital, consider a firm that has debt, D, with a market value of \$300 (6% required return, R_D) and equity, S, with a market value of \$500 (15% required return, R_S). Thus, the weight for the debt, W_D (= D/(D+S)), is 0.375 and that for the equity, W_S (=S/(D+S)), 0.625. This makes the market value of the firm assets, A, equal to \$800 with a combined required return, R_{COMP}, of 11.625%.

$$R_{COMP} = W_D R_D + W_S R_S = 0.375(.06) + 0.625(.15) = 11.625\%$$

R_{COMP} is also equal to the weighted average of the required returns of the non-operating assets and the operating assets as shown below.

$$R_{COMP} = \frac{N}{A}R_N + \frac{O}{A}R_O \qquad (8)$$

In this equation, R_N is the required return of the non-operating assets and R_O of the operating assets. Assume the firm has \$50 in non-operating assets, N, with a required return of 3.6%.[3] Since the total assets for the firm is \$800, the value of the operating assets, O, is \$750. Therefore, N/A=50/800=0.0625 and O/A=750/800=0.9375.

Let R_{ND} and R_{NS} be the required return of debt and equity respectively for the non-operating assets. Given R_N (=3.6%), W_D (=0.375), W_S (=0.625), and based on the ratio of R_D and R_S, 6%/15% (=0.4), R_{ND} and R_{NS} can be found as 1.858% and 4.645% respectively. We assume that $R_{ND}/R_{NS}= R_D/R_S=0.4$.

Based on Equation (8) and given R_{COMP} (=11.625%), R_N (=3.6%), N/A (=0.0625), and O/A (=0.9375), the required return to the operating assets, R_O, is found as 12.16%. Then based on R_O (=12.16%), W_D (=0.375), W_S (=0.625), and assuming $R_{OD}/R_{OS}= R_D/R_S=0.4$, R_{OD} and R_{OS} can be found as 6.276% and 15.69% respectively.

With an effective tax rate, T, of 40%, using Equation (2) results in a $WACC_{COMP}$ equal to 10.725%. Using Equation (2) but based on R_{OD} and R_{OS}, $WACC_O$ is found as 11.219%. This is the appropriate discount rate to find the present value of expected future FCFs, the WACC to calculate EVA, and the discount rate to estimate the NPV of a new project with similar risk of current firm operations.

Currently, the theory of determining a firm's optimal capital structure is based on the market values of the firm's debt and equity. But if the management believes that the market value of the equity does not reflect its true value, in practice, it can use the VBM to determine the value of the equity, then combined with the market value of the debt, to better assess what the optimal debt ratio is. In order to correctly use the VBM, $WACC_O$, instead of $WACC_{COMP}$, should be applied.

In the case where the non-operating assets have more risk than the operating assets, the procedure would be the same. However, unlike the above example, the resulting $WACC_O$ would be lower than $WACC_{COMP}$.

IV: EFFECT OF WACC MISCALCULATION

In order to show the potential effect of the misestimation of WACC, we return to the sample firm in Section III. Assume that, although the market value of the operating assets is \$750, the book value is only \$725. If market and book values are the same for the non-operating assets and the debt, the book value of the equity must be \$475. The MVA calculation would thus yield the correct value of \$25. An efficient market would recognize that $WACC_O$ (11.219%) is the appropriate discount rate. Assuming that EVA is expected to continue from current levels as a perpetuity, EVA is \$2.80475. This is consistent with a NOPAT of \$84.1425. Following the existing literature, management would use $WACC_{COMP}$ and incorrectly estimate EVA as \$6.38625 and

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[3] The market value and required return of the non-operating assets (for example, cash and marketable securities) is normally easier to estimate than that of the operating assets.

MVA as \$59.5455. Using the wrong capital cost gives managers the impression that they are creating a lot more value (238% for MVA and 228% for EVA) than the market valuation indicates.

In the case where the firm has non-operating assets with higher risk than the operating assets the opposite effect would occur. The incorrectly calculated EVA and MVA would be lower than the correctly determined values. Since MVA depends, in effect, on projections based upon the current level of value creation, misestimation of EVA is magnified when considering the MVA. The degree of error in each case is a function of the difference between the risk, required returns, and sizes of the operating and non-operating assets.

V: REVISITING MVA

Finding firm value with $WACC_O$ rather than $WACC_{COMP}$ also has implications for the interpretation of MVA in equation (6). Given the more appropriate focus on the assets that generate the FCF that determine value creation, an improved reformulation of MVA could be

$$MVA = Vo - Book\ Value\ of\ O \qquad (9)$$

where O still refers to the operating assets. To the extent that this additional value from managerial operating decisions increases the market value of the firm's equity, it should be consistent with the original specification of MVA in (6). However, as operating value increases, it is possible that the value of all the firm's market-traded financial claims benefit, and vice versa. This provides an additional useful interpretation of MVA as

$$MVA = Market\ Value\ of\ D\ and\ S - Book\ Value\ of\ Assets \qquad (10)$$

where D and S refer to debt and equity as in Section III. This might depend on the nature of the firm's non-operating assets. In the typical case where they are low risk assets such as cash and marketable securities, equation (10) should suffice. Risky non-operating assets, such as minority interest are more susceptible to fluctuations of market value from book value due to the way minority interest is accounted for by the investing firm. As market value of the minority assets fluctuates, it may take longer for the book value to adjust. This potential problem could be minimized by interpreting MVA as

$$MVA = Market\ Value\ of\ D\ and\ S - N - Book\ Value\ of\ O \qquad (11)$$

Here, N is the estimated market value of the non-operating assets. Each of these new MVA formulations allow for a more precise discussion of the linkage between decision-making and operating value that is the focus of VBM.

V. CONCLUSION

The purpose of the study of Financial Management is to provide linkages between the choices of the decision makers and the value of the firm. The increased sophistication of firm owners, or the financial institutions that serve as the ultimate owner's agents, and of those that study managerial performance calls for more precise estimates of value. Given the importance of the cost of capital, the current real-world treatment of the WACC has been somewhat neglected, both in concept and procedure. The ability to identify the appropriate measure for valuing the operating assets is vital to advances in our understanding. This paper addresses these shortcomings by proposing an appropriate distinction between the treatment of operating and non-operating assets as well as a clear, easily usable procedure for estimating the correct WACC. Although this paper is couched in terms of the most popular Value Based Management tools, the proposed approach to finding WACC has important implications for capital budgeting and the study of capital structure. Advances in these areas are all dependent on accurately measuring and utilizing the firm's cost of capital.

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