Market Timing in Corporate Finance Decisions: Evidence From Stock Market Anomalies

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Abstract

Using an equity mispricing score that incorporates 155 anomaly characteristics, I find that U.S. firms are 59% more likely to issue equity when overvalued and 28% more likely to repurchase shares when undervalued. Moreover, this relationship is more pronounced when executives own more equity in the firm. I also show that executives are more likely to use equity as currency in acquisitions when overvalued and use cash when undervalued. I find consistent evidence using an international dataset that includes 33 countries. These findings provide new evidence about market timing and support the market timing hypothesis.

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1 Introduction

Stock prices can not perfectly reflect the available information because information is costly (Grossman and Stiglitz (1980)). Firm executives are likely to identify when stock prices deviate from the fundamental value. This information asymmetry can create an incentive for executives to maximize long term shareholders' wealth. Executives can maximize long term shareholders' wealth by conducting a seasoned equity offering (SEO) when the firm is overvalued and repurchasing shares when the firm is undervalued. These strategies are called market timing and lead to wealth transfers among investors (Baker and Wurgler (2002); Loughran and Ritter (1995)). However, despite the extensive literature, it is empirically hard to identify stock mispricing; hence, it remains a challenge to test whether executives engage in market timing (Baker, Ruback, and Wurgler (2007), Khan, Kogan, and Serafeim (2012), and Dong, Hirshleifer, and Teoh (2012)). To identify stock mispricing, earlier studies use both ex-ante and ex-post measures such as market-to-book (M/B) ratio, past abnormal returns, and future abnormal returns. However, these measures are still under debate. For example, M/B ratio and past returns might reflect growth opportunities that can also affect corporate finance decisions (Baker, Ruback, and Wurgler (2007)). In addition, future abnormal returns following firms' financial decisions might be a result of change in firm risk.[1] These studies show that we need a more reliable mispricing measure to test the market timing hypothesis.

I contribute to the literature by testing the market timing hypothesis using a mispricing score that incorporates 155 stock market anomalies. Using this measure, I show that firm mispricing impacts market timing behavior in issuances and repurchases. I also document that market timing behavior is related to executives' personal benefits. To further gain confidence in my findings regarding market timing, I test whether executives time the market in mergers and acquisitions (M&A). I find that executives use equity as currency in M&A transactions when the stock is overvalued and cash when the stock is undervalued.

[1] See, for example, Carlson, Fisher and Giammarino (2006); Carlson, Fisher, and Giammarino (2010), Eckbo, Masulis, and Norli (2000), Brav, Michaely, Roberts, and Zarutskie (2009).

A stock market anomaly is defined as a firm characteristic that shows return predictability in the cross-section. Existing literature documents that these firm characteristics are likely to reflect mispricing. For example, McLean and Pontiff (2016) show that the return predictability of a stock market anomaly becomes weaker after the anomaly is published in an academic journal. They argue that arbitrageurs become aware of anomaly characteristics in published articles and then correct any mispricing in the market. Moreover, Bowles, Reed, Ringgenberg, and Thornock (2020) show that after a short period of disclosure of anomaly characteristics, investors quickly react to the new information and correct most of the mispricing. This evidence also suggests that anomalies represent mispricing and arbitrageurs react to the financial disclosures.

These findings provide evidence that anomalies are likely to represent mispricing. However, using a single anomaly would be a noisy measure of mispricing. Therefore, I test the market timing hypothesis using a mispricing score that incorporates 155 continuous anomaly characteristics studied by Chen and Zimmermann (2021). My measure extends the Stambaugh, Yu, and Yuan's (2015) measure based on 11 anomaly characteristics that they use to study the idiosyncratic volatility (IVOL) puzzle.

Using this mispricing score, I first test whether executives use market timing strategies in their SEO decisions. In the sample period between 1980 and 2019, I find that a one standard deviation increase in the mispricing score (i.e., more overvaluation) leads to a 59% increase in the probability of an SEO in the next quarter, and a 16% increase in the total shares issued in an SEO to total shares outstanding ratio, relative to the unconditional means. I also investigate whether market timing has any impact on the fees paid to the investment banks. My hypothesis is that when executives issue equity when the stock is overvalued, investment banks would also identify overpricing at least partially. Therefore, they would ask higher fees since marketing overvalued equity would be more difficult. Executives are likely to accept these higher fees since the gain from market timing would outweigh the investment bank fees which are typically around 5%. In line with this hypothesis, I find that a one standard deviation increase in the mispricing score leads to a 7% increase in the investment bank fees relative to the mean.

Since market timing is selling overvalued equity and buying undervalued equity, I also investigate whether executives repurchase shares when the firm is undervalued in the stock market. I find that a one standard deviation decrease (i.e., more undervaluation) in the mispricing score leads to a 28% increase in the probability of a share repurchase in the next quarter; and with a 10% increase in the total shares repurchased to total shares outstanding ratio relative to the unconditional means.

To further validate my findings, I divide the 155 anomalies underlying my mispricing score into two groups corresponding to published and not yet published depending on whether the sample year is before or after the publication year of the anomaly. I then create two mispricing scores at the beginning of each quarter: $Mispricing\ Score_{published}$ and $Mispricing\ Score_{unpublished}$. For example, to calculate $Mispricing\ Score_{unpublished}$ ($Mispricing\ Score_{published}$) for a given stock in the year 2006, I use the anomalies that are published after (before) 2006. This decomposition is motivated by the finding in McLean and Pontiff (2016) that an anomaly is likely to represent a stronger mispricing before it is published in an academic journal. Since the publication date is uncorrelated with firms' economic fundamentals, this decomposition allows for an exogenous change in the mispricing measure. I expect that anomalies have more explanatory power in SEO/repurchase decisions before the publication date because they are likely to represent stronger mispricing. Consistent with my hypothesis, I find that both measures significantly explain the SEO/repurchase decision, but that the mispricing score that is created using unpublished anomalies has a significantly larger effect. This finding strengthens the hypothesis that executives engage in market timing in their financial decisions.

While my results show that executives' mispricing signals are strongly correlated with anomaly characteristics, it is likely that such mispricing signals are more strongly correlated with some types of anomalies than with others. Executives are more likely to identify mispricing from a firm's financial statements. Therefore, executives' mispricing signals are more likely to be correlated with anomalies related to balance sheet or income statement items (i.e., accounting anomalies) than with other anomalies. To test this hypothesis, I classify anomalies as either an accounting anomaly or other anomaly based on the anomaly groups created by Chen and Zimmermann (2021). At the beginning of each quarter, I create two mispricing scores using the anomalies in each group and test the relationship between the SEO/repurchase decision and the two mispricing scores. Consistent with the hypothesis, I find that the mispricing score that is constructed using accounting anomaly characteristics has both economically and statistically significantly higher explanatory power than the mispricing score that is constructed using other types of anomalies in SEO/repurchase decisions.

I also investigate whether executives' incentives have any effect on market timing. Since existing shareholders benefit from market timing, executives would have more incentive to time the market when they own a large amount of equity in the firm. To examine this, I estimate the magnitude of the relationship between the SEO/repurchase decision and mispricing for different levels of equity ownership by executives. I find that when CEOs own more equity, they are more sensitive to mispricing in the SEO/repurchase decision; i.e., they are more sensitive to overpricing (underpricing) in issuing (repurchasing) equity when they hold a larger fraction of shares as a fraction of their total compensation. Specifically, following a one standard deviation increase (decrease) in the mispricing score, firms with CEOs in the top tercile of ownership are 55% (33%) more likely to issue (repurchase) equity than those in the bottom tercile of ownership. My results are robust to using the average ownership ratio of all executives, controlling for executives' unvested shares, and defining equity ownership as the sum of vested and unvested shares instead of using only vested shares.

Next, I investigate whether executives time the market in their mergers and acquisition (M&A) decisions. Shleifer and Vishny (2003) argue that rational managers rationally respond to less-than-rational markets by acquiring firms using overvalued equity. Motivated by this argument, I test the relation between mispricing score and two groups of M&A activities separately. The first group includes the transactions in which the acquiror uses equity as currency; the second group includes the transactions in which the acquiror uses cash as currency. I find that when firms are overvalued, they are more likely to use equity and when they are undervalued, they are more likely to use cash. These findings also support the hypothesis that executives time the market in corporate finance decisions.

My results show a robust relationship between the SEO/repurchase decision and the mispricing score for U.S. firms. In spirit of Fama and French (1998), I test the external validity of these results around the world. By using an international dataset that provides anomaly characteristics for each stock-month observation (Jensen, Kelly, and Pedersen (2022)), I extend my method and create a mispricing score using anomaly characteristics for each international firm. I also obtain firm-initiated issuances from the SDC database. Then, I examine the market timing hypothesis using the stocks from 33 countries. I find that executives are more likely to issue (repurchase) equity when the equity is overvalued (undervalued) in other countries as well. Moreover, the economic significance of this relationship is sizable. A one standard deviation increase (decrease) in the mispricing score leads to a statistically significant 7.5% (16.6%) increase in the likelihood of SEOs (share repurchases). These findings confirm that executives around the world use market timing strategies and these strategies are not confined to U.S. firms.

My study is related to McLean, Pontiff, and Reilly (2022) who examine how different types of stock market investors trade according to anomaly characteristics. Their paper finds that only insurance companies and firms are smart in that they sell more shares when stocks are overvalued. In their analysis, they use changes in number of shares outstanding to measure the trading activity of firms. However, a direct test of market timing hypothesis requires a refined measure. As shown by McKeon (2015), increases in the number of shares outstanding include many issuances initiated by employees that are not related to market timing. Indeed, using changes in number of shares outstanding, the evidence in McLean, Pontiff, and Reilly (2022) suggests that even undervalued firms issue equity, which casts doubt on the market timing hypothesis. If firms engage in market timing, I expect to find a relation between mispricing and the component of change in number of shares outstanding that is truly related to the SEO decisions of firm executives. Consistent with my hypothesis, I find that my mispricing measure explains SEO decisions but does not explain employee-initiated issuances. Furthermore, I show that market timing behavior is related to executives' incentives and extends to a firm's M&A decisions. These findings further support the market timing hypothesis.

My study is also related to recent studies that propose new mispricing measures to test the market timing hypothesis. For example, Khan, Kogan and Serafeim (2012) use mutual fund flow-driven purchases as an indicator of overvaluation and find that the probability of an SEO increases for the affected stocks in the following four quarters. Berger (2021) shows, however, that flow driven price increases might not capture mispricing. In another study, Dong, Hirshleifer and Teoh (2012) propose to identify mispriced stocks using the forward-looking residual income model of Ohlson (1995). However, a debate remains about the return predictability of this model and whether the model represents an omitted risk factor (Chen and Zimmermann (2021) and Hwang and Lee (2013)). Moreover, the cross-sectional predictability of future returns using a single variable may be unreliable since the anomaly literature documents more than 300 such variables. I build on these works by testing the market timing hypothesis using a new mispricing measure based on 155 anomaly characteristics. To further highlight my contribution to the market timing literature, I orthogonalize my mispricing measure with respect to the existing measures. I find that the orthogonalized version of my mispricing score still explains SEO and share repurchase decisions. Furthermore, the magnitudes of the estimated coefficients of the orthogonalized versions of my mispricing score are very similar to the magnitude of the unorthogonalized mispricing score. These findings characterize the novel feature of my mispricing measure and show that its predictive ability for SEO and share repurchase decisions improves upon that of existing measures.

2 Data and Variables

2.1 Sample Construction

My sample includes all common stocks (share code 10 or 11) that are listed in NYSE, Amex or Nasdaq between 1980-2019. I obtain SEO sample from Thomson Financial's SDC Platinum database. I exclude all private placements, right offerings, and unit offers from the sample similar to Eckbo, Masulis, and Norli (2000). I create my share repurchases sample by calculating the changes in the split-adjusted shares outstanding from CRSP database (Stephens and Weisbach (1998)). The share repurchase sample period starts in 1982 because there were no explicit rules directly regulating share repurchases in the United States until that time; therefore, there was a risk of SEC investigation of market manipulation for firms undertaking share repurchases before 1982 (Grullon and Michaely (2002)). I use CRSP dataset for market related data and Compustat for accounting variables. I create executive ownership variables by using Execucomps database. I obtain factor returns and risk-free rates from Kenneth French's website. My analysis is at quarter level; therefore, all frequencies reflect the relevant corporate decision in a quarter. The final sample includes 7,482 SEOs and 83,607 share repurchases.

2.2 Mispricing Measure

Empirical tests of the market timing hypothesis require a reliable measure of mispricing, therefore faces a significant challenge. The existing literature uses several mispricing measures, but each of them is still debated. The main potential issue with the existing measures is endogeneity. Existing measures are likely to be correlated with likelihood of firms' financial decisions, therefore it is not conclusive whether these measures represent mispricing or the correlation with the likelihood of financial decisions. The second issue is that existing mispricing measures are likely to be correlated with changes in risk, therefore it is hard to distinguish between risk and mispricing. By using an equity mispricing score that incorporates 155 anomaly characteristics, I aim to minimize endogeneity concerns and risk-based explanations. In this section, I first summarize the widely used mispricing measures and review the ongoing discussion about the need for a better mispricing measure to test the market timing hypothesis. Then, I introduce my mispricing measure and its advantages over the existing measures.

A strand of literature uses ex-ante mispricing measures to test the market timing hypothesis. For example, Eckbo and Masulis (1995) find evidence that new issues occur after a significant run-up in the issuer's stock price. The relation between price run-up and SEO decision would support the market timing hypothesis. Baker and Wurgler (2002) uses the Market to Book (M/B) ratio as a mispricing measure and explain how market timing affects firms' capital structure. This paper claims that using M/B ratio allows a comparison between the market price and a benchmark fundamental value, which is proxied by the book value of assets, and differences between market price and book value is attributed to mispricing. However, both past returns and M/B ratios are likely to be correlated with firm characteristics that are also correlated with SEO or share repurchase decision such as firm's investment opportunities. For example, a firm with valuable investment opportunities might experience a price run-up before the SEO decision and implement these investment opportunities by issuing equity. In addition, since book value is a backward-looking measure, any price run-up resulting from a future investment opportunity would increase the M/B ratio (Tobin (1969)). In this case, the documented relationship between mispricing measure and corporate financial decisions might not be due to market timing.

As an alternative to using prior returns, another strand of literature uses future abnormal returns to measure mispricing at the time of SEO or share repurchase (e.g., Ikenberry, Lakonishok, and Vermaelen (1995); Loughran and Ritter (1995)). These studies suggest that if a firm is overvalued (undervalued) at the time of a corporate financial decision (SEO or share repurchase), the future abnormal returns should be lower (higher) so that prices converge to the fundamental value. The underlying assumption in these studies is that firm risk remains constant after the SEO/repurchase decision. However, positive or negative future abnormal returns might be related to rational expectations about the firm's value rather than being related to deviations from the fundamental value. For example, if the firm risk is changing around SEO and share repurchase events, then future abnormal returns compared to an ex-ante benchmark might reflect changes in the firm risk. As argued by Eckbo, Masulis, and Norli (2000), equity issuance lowers systematic risk exposure by reducing leverage, thereby also reducing exposure to unexpected inflation and default risks. Thus, lower risk is likely to drive future lower returns rather than overvaluation at the time of an SEO. In addition, there is still an ongoing discussion about how to properly calculate and test future abnormal returns. For example, Mitchell and Stafford (2000) shows that although many papers use buy and hold returns to calculate future abnormal returns, this method is likely to be flawed.

There are two more recent papers that propose new mispricing measures and test the market timing hypothesis. The first study is Khan, Kogan, and Serafeim (2012). This paper uses flow driven purchases by mutual funds as an indicator of overvaluation. The underlying assumption in this study is that prices reflect fundamental values before flow-driven purchases and that these purchases cause the stocks to be overvalued. The paper argues that a mispricing measure driven by investors is relatively exogenous to the firm characteristics and does not raise endogeneity concerns. In contrast, Berger (2021) shows that mispricing measures using mutual fund flows might not be capturing mispricing due to selection bias: Mutual funds select which stocks to buy (sell) following an inflow (outflow), therefore the criteria for the selection might be correlated with the SEO/repurchase decision. Berger (2021) argues that after accounting for this selection bias, the relation between market mispricing and a firms' financial decisions disappears.

The second study is Dong, Hirshleifer and Teoh (2012). This paper adopts an alternative fundamental value measure (V) and use the M/V ratio instead of the M/B ratio to identify mispriced stocks. More specifically, this paper uses the residual income model of Ohlson (1995), which uses analyst forecasts to derive a forward-looking measure of fundamental value. Therefore, the M/V ratio filters the effects of future investment opportunities from the market prices and is shown to predict future abnormal returns (Frankel and Lee (1998)). However, it is still empirically difficult to rule out concerns that the return predictability of Ohlson's (1995) model might be driven by omitted risk factors. For example, Hwang and Lee (2013) find supporting evidence that this measure is likely to capture risk rather than mispricing. In addition, Chen and Zimmermann (2021) find mixed results regarding the future return predictability of this model.

Overall, existing mispricing measures that are used to test the market timing hypothesis are still hotly debated, and there is no conclusive result yet. I contribute to this literature by using a mispricing score incorporating a large set of anomalies that show return predictability. My mispricing measure extends the Stambaugh, Yu and Yuan (2015) measure, which is based on 11 anomaly characteristics and is used to study IVOL puzzle. I use 155 continuous anomaly characteristics in Chen and Zimmermann (2021)[2] and create a single mispricing score for each stock-month observation. I list all the anomalies that I use to construct my mispricing score in Table A1

At the beginning of each quarter, I calculate the percentile ranking of each stock for each anomaly characteristic. Thus, each stock has a percentile ranking between 0 and 1 for each anomaly. If higher values of an anomaly characteristic represent undervaluation, I multiply the values for that characteristic by -1. This makes all anomalies consistent in the sense that high values represent overvaluation. If the stock has a missing value for a characteristic, then I replace the missing value with the median value of that characteristic in that month. After calculating percentile rankings, I calculate the equally weighted average of these percentile rankings for each stock-month to obtain a single mispricing score. This mispricing score has the advantage of using many characteristics, therefore is not dominated by a single anomaly. Since many mispricing signals are used together, this score is a more comprehensive measure of mispricing compared to any single anomaly characteristic.

[2] https://www.openassetpricing.com/

One might argue that anomalies might not represent mispricing and be a compensation for omitted risk factors. However, there is evidence in the literature that anomalies are likely to represent mispricing. For example, McLean and Pontiff (2016) show that many firm characteristics can predict future returns and most of the anomaly returns either vanish or has an alpha decay after the academic publication. This finding implies that anomalies represent mispricing and mispricing has been corrected after the anomalies are publicized broadly. Moreover, Bowles, Reed, Ringgenberg, and Thornock (2020) show that after a short period of anomaly characteristics disclosure, investors quickly react to the new information and correct most of the mispricing very quickly. If these returns were spurious, we would not expect to see any reaction to financial disclosures.

To show the return predictability of this mispricing measure, I sort firms into quintile portfolios according to mispricing score at the beginning of each month and observe the market value weighted returns of each portfolio in the following month. After obtaining time series of portfolio returns for each quintile, I regress portfolio returns on Fama French 3 factor returns and report the estimated coefficients from this regression in Table 1 1. This table shows that undervalued stocks deliver 0.21% monthly risk adjusted returns. In addition, overvalued stocks deliver -0.55% monthly risk adjusted returns. The spread portfolio, therefore, deliver 0.76% monthly risk adjusted returns. All these results are statistically significant at 1% level. These results confirm that a composite mispricing measure using anomaly characteristics predict future risk adjusted returns in the full sample period.

3 Results

3.1 SEO and Share Repurchase Decision

3.1.1 Main Specifications

I start my main analysis by testing the relation between probability of SEO/repurchase decision and the mispricing score. To investigate this relation, I estimate a linear probability model with high dimensional fixed effects. Linear probability models allow me to include industry by quarter fixed effects to control for unobservable variation across industries at each cross section and across time for a given industry. The estimated model is as follows:

$$\text{Firm Decision}_{i,t+1} = \beta_0 + \beta_1 \times \text{Mispricing Score}_{it} + \text{Controls}_{it} + \gamma_{jt} + \epsilon_{it} \tag{1}$$

I estimate the model above for two different firm decision dependent variables. The first firm decision variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. The second firm decision variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. The "Controls" include the beginning of quarter values of B/M ratio, B/M, "Past 12m Net of Market Return", return on asset (ROA), "Cash by Asset", market capitalization, "Leverage","Dividend yield", "Volatility", "Change in the volatility (Δ Volatility), and "Firm Age" as explained in detail in the Appendix B. I also include industry by quarter fixed effects (γ_{jt}). I cluster the standard errors at the year level. In addition to SEO/repurchase decision, I also estimate the relation between mispricing score and shares issued (repurchased) to the total shares outstanding ratio. To estimate this relation, I replace the "Firm Decision" dependent variable with the associated ratio for SEOs and share repurchases separately.

For issuances, I conduct two more analyses. My first analysis tests the relation between mispricing and employee-initiated issuances. By using changes in number of shares outstanding as a measure of firm trade, McLean, Pontiff, and Reilly (2022) find that firms sell more shares when stocks are overvalued. However, changes in number of shares outstanding is a noisy measure of issuance because it includes many cases initiated by employees (McKeon (2015)). Since employee compensation decision is made years prior to issuance, only the firm-initiated component is related to market timing. For example, using the changes in number of shares outstanding measure, the evidence in McLean, Pontiff, and Reilly (2022) suggests that even undervalued firms issue equity, which casts doubt on market timing hypothesis. If firms engage in market timing, I expect to find a relation only between SEO decision and mispricing measure, and not between employee-initiated issuances and mispricing score. To test the relation between employee-initiated issuances and mispricing score, I follow McKeon (2015) and create an employee-initiated issuance indicator variable that is equal to 1 if number of shares outstanding increases less than 2% in a quarter and equal to 0 if there is no change. Then, I replace my dependent variable in Equation(1) with this indicator variable and estimate the equation. My second analysis investigates whether market timing has any implication on the fees paid to the investment banks. Since marketing overpriced shares would be more difficult, investment banks would ask higher fees from market timers. To estimate this relation, I replace the dependent variable with the logarithm of gross spread, calculated as the fees paid to the investment banks divided by total proceeds. The dataset does not include gross spread value for all SEOs, therefore my sample for this analysis includes 6,906 SEOs. I document all of the findings in Table 2.

In Panel A, I report the estimated coefficients and standard errors from Equation (1) by using "SEO" as "Firm Decision" variable. I find that a one standard deviation increase in mispricing score (more overvaluation) leads to a 58.8% increase in the likelihood of SEOs relative to its unconditional probability. Moreover, one standard deviation increase in mispricing score leads to a 15.6% increase in the shares issued to the total shares outstanding ratio relative to its mean. When I use employee-initiated issuance indicator as a dependent variable, I do not find a significant relation between mispricing and employee-initiated issuance. This finding supports the idea that mispricing explains only firm-initiated issuances consistent with the market timing hypothesis. Finally, I document the relation between mispricing score and gross spread and find that a one standard deviation increase in mispricing score leads to 6.4% increase in the total paid fees, relative to the mean.

In Panel B, I report the estimated coefficients and standard errors from Equation (1) by using "Share Repurchase" as "Firm Decision" variable. I find that a one standard deviation decrease in mispricing score (more undervaluation) leads to 27.9% increase in the likelihood of share repurchases relative to its unconditional probability. I also find that a one standard deviation decrease in mispricing score leads to 9.6% increase in the shares repurchased to the total shares outstanding ratio relative to its mean.

These results show that overvalued firms are more likely to issue equity and undervalued firms are more likely to repurchase shares. Moreover, the relation between mispricing score and the shares issued (repurchased) to total shares outstanding ratio is also positive (negative), further confirming that overvalued (undervalued) firms are more likely to issue (repurchase) more equity.

3.1.2 Decomposing Mispricing Score: Published vs Unpublished Anomalies

McLean and Pontiff (2016) document that most of the anomalies have alpha decay after the publication of these anomalies in the academic journals. This finding implies that return predictability of the anomalies is stronger before the publication date. Publication dates are exogenous to the firm decision variables, therefore the changes in mispricing score are exogenous to the firm decision variables. I exploit the variation in publication dates by creating two mispricing scores. I split anomalies into two groups as "Published" and "Unpublished" depending on the publication date at the beginning of each sample year. Then, I create two separate mispricing score using the anomalies in each group. For example, $MispricingScore_{unpublished}$ ($MispricingScore_{published}$) in January 2006 is created using the anomalies that are published after (before) 2006. By using these mispricing scores, I estimate Equation(1) again. Then, I add two mispricing scores together and repeat my estimation. I report the results in Table 3.

Panel A reports the estimated coefficients of mispricing scores when the firm decision variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. In the first column, I use the mispricing score created by using published anomalies and in the second column, I use the mispricing score created by using unpublished anomalies. The third column reports the coefficients when I add both mispricing scores together. These result show that a one standard deviation increase in "Mispricing Score (Unpublished)" leads to higher likelihood of SEOs compared to "Mispricing Score (Published)" (0.51 vs 0.26). When I estimate the same model by including both mispricing scores together, the difference becomes larger (0.49 vs 0.10). Finally, I test the equality of the estimated coefficients of "Mispricing Score (Unpublished) and Mispricing Score (Published) and report the results in the last column. I find that I can reject the equality of these two mispricing scores at 1% statistical significance.

Panel B reports the estimated coefficients of mispricing scores when the firm decision variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. Similar to Panel A, each column represents a model including "Mispricing score (Unpublished)", or "Mispricing score (Published)" or both of them together. I find that a one standard deviation decrease in "Mispricing Score (Unpublished)" leads to higher likelihood of share repurchases compared to "Mispricing Score (Published)" (3.23 vs 2.66). When I estimate the same model by including both mispricing scores together, the difference becomes larger (2.92 vs 1.48). Finally, I test the equality of the estimated coefficients of "Mispricing Score (Unpublished) and Mispricing Score (Published) and find that I can reject the equality of these two mispricing scores at 5% statistical significance.

These findings suggest that an anomaly based mispricing score explains firm decisions when the anomalies that are used to construct mispricing score represent stronger mispricing. These results further support the hypothesis that executives are more likely to issue equity when the firm is overvalued and repurchase shares when undervalued.

3.1.3 Decomposing Published Anomalies

In Section 3.1.2, I document that the mispricing score created by using unpublished anomalies has higher explanatory power in both SEO and share repurchase decisions compared to the mispricing score created by using published anomalies. To refine this test, I investigate whether it matters the publication date is near or far among published anomalies. Since anomalies represent weaker, if any, mispricing many years after the publication, a mispricing score using the anomalies that are published long before the sample date should have a very small explanatory power, if any, in SEO or share repurchase decision. In addition, I would also argue that the mispricing score using unpublished anomalies should have a similar or slightly higher explanatory power than a mispricing score using the anomalies that are published shortly before the sample date.

To empirically test these arguments, I create 3 different mispricing scores. The first mispricing score is created by using unpublished anomalies at each sample date. This measure is identical to the "Mispricing Score (Unpublished)" that is explained in Section 3.1.2. The second measure uses the anomalies that are published maximum 10 years before the sample date ("Mispricing Score ($Published < 10years$)"). The last mispricing score uses the anomalies that are published more than 10 years before the sample date ("Mispricing Score ($Published >= 10years$)"). I estimate the Equation(1) by using these three mispricing scores separately. I also augment the same model with all of the three mispricing scores together and estimate the relation between mispricing scores and SEO/repurchase decision. I report the estimated coefficients and standard errors in Table 4.

Panel A reports the estimation results when the dependent variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. Panel B reports the estimation results when the dependent variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. In each panel, I document that the relation between SEO/repurchase and the mispricing score is largest when I use Mispricing Score (Unpublished). This finding is consistent with McLean and Pontiff (2016) who show that anomalies represent stronger mispricing before the publication in academic journals. I also find that the relation between SEO/repurchase decision and "Mispricing Score

($Published >= 10years$)" is not statistically significant. These findings are also consistent with the literature that shows that anomalies are corrected after the publication and do not represent a mispricing as strong as they do before the publication. Moreover, when I include all mispricing scores in the same model, I find that Mispricing Score (Unpublished) still has the largest explanatory power in SEO/repurchase decision with 1% statistical significance and "Mispricing Score ($Published >= 10years$)" still does not retain statistical significance neither in SEOs nor in share repurchase decisions.

Finally, I test the equality of coefficients of i) "Mispricing Score (Unpublished)" and "Mispricing Score ($Published < 10years$)" and ii) "Mispricing Score ($Published < 10years$)" and "Mispricing Score ($Published >= 10years$)". Consistent with my hypothesis, the equality of estimated coefficients of "Mispricing Score (Unpublished)" and "Mispricing Score ($Published < 10years$)" can be rejected at 5% in Panel A and at 10% in Panel B. This result is likely to be due to alpha decay happening gradually. However, the equality of estimated coefficients of "Mispricing Score ($Published < 10years$)" and "Mispricing Score ($Published >= 10years$)" can be rejected at 5% statistical significance in Panel A and 1% statistical significance in Panel B. This result shows that explanatory power of anomaly based mispricing scores are different in SEO/ repurchase decisions depending on the strength of mispricing they represent.

These results further confirm that an anomaly based mispricing score explains SEO/repurchase decision consistent with the market timing hypothesis. Moreover, anomaly based mispricing score explains these corporate decisions only when the anomalies represent stronger mispricing and loses its explanatory power if anomalies that are published long before are used to create a mispricing score.

3.1.4 Decomposing Mispricing Score: Accounting Anomalies vs Other Anomalies

In the previous sections, I show that mispricing score significantly explains SEO and share repurchase decisions, confirming the market timing hypothesis. However, executives' mispricing signals might not be correlated with all types of anomalies. In this case, the relation between SEO/repurchase decision and the mispricing score that is created by using certain type of anomalies should be higher. Executives are likely to infer any mispricing from firm's financial statements, therefore anomaly characteristics that are calculated by using balance sheet or income statement items are potential candidates to be highly correlated with the executives' mispricing signals.

To test this hypothesis, I investigate whether a mispricing score using accounting anomalies has higher explanatory power in SEO/repurchase decisions compared to a mispricing score using all other anomalies. To study this, I split anomalies into two groups as "Accounting" and "Other" anomalies using the anomaly classification in Chen and Zimmermann (2021). Then, I create two mispricing scores using the anomalies in each group. I estimate Equation (1) by including "Mispricing Score (Accounting)" and "Mispricing Score (Others)" separately and then both of them together. I report the estimated coefficients and standard errors in Table 5. Panel A reports the estimated coefficients of mispricing scores when the firm decision variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. Panel B reports the estimated coefficients of mispricing scores when the firm decision variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. In each panel, first two columns report the estimation results when each mispricing score is included in the model one at a time and the last column reports the estimation results when both mispricing scores are included in the model together.

Consistent with my hypothesis, I document that the magnitude of the estimated coefficients of "Mispricing Score (Accounting)" are larger compared to the that of "Mispricing

Score (Others)" for both SEO and share repurchase decisions. For SEOs, the estimated coefficient of Mispricing Score (Accounting) is equal to 0.71 and the estimated coefficient of Mispricing Score (Others) is equal to 0.30. For share repurchases, the estimated coefficient of Mispricing Score (Accounting) is equal to -3.72 and the estimated coefficient of Mispricing Score (Others) is equal to -2.29. Both coefficients are statistically significant at 1% level in each model. In the last column of each Panel, I add two mispricing score together and test the relation between SEO/repurchase decision and these mispricing scores. I find that coefficients of "Mispricing Score (Accounting)" retain statistical significance at 1% level but "Mispricing Score (Other)" retains statistical significance only in Panel B. has a larger coefficient than "Mispricing Score (Others)". Even in Panel B, "Mispricing Score (Accounting)" has a larger explanatory power in share repurchase decision compared to "Mispricing Score (Other)". I can reject the equality of coefficients of "Mispricing Score (Accounting)" and "Mispricing Score (Other)" at 1% statistical significance level. Overall, these findings also support the hypothesis that executives respond to mispricing signals and their signals have higher correlation with the mispricing score that is created by using Accounting anomalies than the mispricing score that is created by using all other anomalies.

3.2 The Effect of Executives' Equity Ownership on Market Timing

Market timing benefits long term existing shareholders because a market timer firm sells overpriced equity to the new shareholders or repurchase underpriced equity from short term shareholders. However, if executives do not have any personal benefit, then there would be very limited or no motivation for them to use market timing strategies. Therefore, we can argue that as executives gain more personal benefit from market timing, they would become more sensitive to the mispricing signals in their SEO and share repurchase decisions.

Existing literature shows that executives' personal benefits would affect corporate decisions. For example, Bergstresser and Philippon (2004) show that accruals management increases as the CEO's compensation becomes more sensitive to current share prices. A similar argument can be made in the market timing context. Executives' SEO and share repurchase decisions can be affected by their personal benefits. To investigate this, I study whether the executives are more sensitive to mispricing signals when they have more equity in the firm. A simple formulation of a CEO's personal benefits from issuing equity (share repurchase) when the stock price is above (below) the fundamental value is as follows:

The number of shares outstanding is equal to N1 and the current price is equal to either P1 or P2. Fair price of the stock, P0, which is less than P1 and greater than P2. Market value of the firm is the multiplication of price and total shares outstanding, N1*P0. If CEO owns α fraction of total shares, her total ownership is equal to α*N1. CEO can either do nothing, issue equity if price is equal to P1, or repurchase shares if price is equal to P2. I calculate the final total ownership for each case:

i) Do Nothing:

$$TotalOwnership = P_0 * \alpha * N_1 \tag{2}$$

ii) Issue β fraction of total shares outstanding, N1*β:

$$\begin{aligned} TotalOwnership &= \frac{\alpha * N1}{N1(1+\beta)} * [N1 * P0 + P1 * N1 * \beta] \\ &= \frac{\alpha * N1}{1+\beta} * [P0 + P1 * \beta] \end{aligned} \tag{3}$$

$$\frac{\partial TotalOwnership}{\partial \beta} = \frac{\alpha * N1 * (P1 - P0)}{(1+\beta)^2} > 0 \tag{4}$$

iii) Repurchase β fraction of total shares outstanding, N1*β:

$$
\begin{aligned}
TotalOwnership &= \frac{\alpha * N1}{N1(1-\beta)} * [N1 * P0 - P1 * N1 * \beta] \\
&= \frac{\alpha * N1}{1-\beta} * [P0 - P1 * \beta]
\end{aligned} \tag{5}
$$

$$
\frac{\partial TotalOwnership}{\partial \beta} = \frac{\alpha * N1 * (P0 - P1)}{(1-\beta)^2} > 0 \tag{6}
$$

I start my analysis by calculating firm executives' ownership in the firm. I obtain equity ownership data from Execucomp and increase my sample period back to 1980 by using the dataset of Frydman and Saks (2010). I sum total dollar value of equity and vested option ownership to calculate total ownership. When the option ownership data is missing, I replace the total ownership value with equity ownership only. However, using total ownership value to study incentives would be misleading because a similar dollar gain from market timing for a very large firm executive would be very different from that for a very small firm executive. Therefore, I scale total ownership value by total executive compensation in the end of the most recent fiscal year. The most ideal denominator to scale total ownership would be executives' total wealth. However, we do not directly observe executives' wealth. Therefore, I use total compensation in the most recent fiscal year as a proxy for total wealth. This scaling allows me to compare incentives of executives of firms with different market capitalizations. After obtaining total equity ownership to total compensation ratio, I sort firms into terciles based on this ratio at the beginning of each quarter. Then, I add "Equity Ownership" tercile dummy variables and interaction of these tercile dummy variables with the mispricing score into the Equation (1). I hypothesize that interaction of the mispricing score with the highest tercile dummy variable should be positive for SEOs and negative for share repurchases, suggesting that higher equity ownership makes executives more sensitive to the mispricing signals in their SEO and share repurchase decisions. The estimated equation is as follows:

$$
\begin{aligned}
\text{Firm Decision}_{i,t+1} = \beta_0 + \beta_1 \times \text{Mispricing Score}_{it} + \beta_2 \times \mathbb{1}_{EquityOwnership_{i,t}=2} \\
+\beta_3 \times \mathbb{1}_{EquityOwnership_{i,t}=3} + \beta_4 \times \mathbb{1}_{EquityOwnership_{i,t}=2} \times \text{Mispricing Score}_{it} \\
+\beta_5 \times \mathbb{1}_{EquityOwnership_{i,t}=3} \times \text{Mispricing Score}_{it} + \text{Controls}_{it} + \gamma_{ijt} + \epsilon_{it}
\end{aligned}
\tag{7}
$$

I report estimated coefficients and associated standard errors in Table 6. Panel A shows that a one standard deviation increase (decrease) in mispricing score makes the firms with CEOs in the highest equity ownership tercile 55% (33%) more likely to issue shares (repurchase shares) compared to the firms with CEOs in the lowest equity ownership tercile. The results are statistically significant at 1% level and confirm that executives use market timing strategies even more heavily when they own more equity in the firm.

Although CEO is the top executive in the firm, one might argue that he/she does not make all the decisions on his/her own. Instead, other executives would affect these decisions or CEO might delegate some decision-making responsibilities to the other executives. Therefore, other executives' ownership levels may also affect the sensitivity of SEO/repurchase decision to firm mispricing. To investigate whether including other top executives' ownership in the firm affects market timing strategies, I first calculate equally weighted average of equity ownership to total compensation ratios across all executives. Then, I sort firms into terciles based on this measure at the beginning of each quarter. Finally, I repeat the same analysis that I conduct for CEOs by replacing "Equity Ownership (CEO)" variable with "Equity Ownership (All)" variable. I report the results in Panel B of Table 6.

I find that a one standard deviation increase (decrease) in mispricing score makes the firms with executives in the highest average equity ownership to compensation tercile 75% (57%) more likely to issue shares (repurchase shares) compared to the firms with executives in the lowest tercile. These findings confirm that SEO and share repurchase decisions are more sensitive to mispricing when the top executives on aggregate own more equity in the firm.

4 The Effect of Market Timing on Mergers and Acquisitions

I also investigate whether executives time the market in their mergers and acquisition (M&A) decisions. In an acquisition, acquiring firm can use equity, cash, or combination of these two payment methods. Firm executives can time the market by using overvalued equity as a currency in their acquisitions (Shleifer and Vishny (2003)). Using overvalued equity as currency would create a wealth transfer from target firm's shareholders to acquiring firm's shareholders. Similarly, if a firm is undervalued, then executives would use cash as currency instead of equity. Motivated by this argument, I test the relation between mispricing score and two types of acquisitions separately. First type of acquisitions include the transactions in which acquiror uses equity as a payment method. Second type of acquisitions include the transactions in which acquiror uses cash as a payment method. I hypothesize that when acquiring firm is overvalued, executives would prefer to pay with overvalued equity. Similarly, when the acquiring firm is undervalued, executives would prefer to pay with cash instead. I report the estimated coefficients and standard errors in Table 7.

My analysis documents that acquiring firm is 34% more likely to make a stock-based acquisition following a one standard deviation increase in the mispricing score, relative to the unconditional mean. In addition, I also show that acquiring firm is 10% more likely to make a cash-based acquisition following a one standard deviation decrease in the mispricing score. I can reject the equality of these results at 1% significance level. These findings further support the hypothesis that executives time the market in corporate financial decisions.

5 International Evidence

In the previous sections, I documented supporting evidence for the market timing hypothesis for U.S. firms. However, there might a potential concern about the external validity of these results. In spirit of Fama and French (1998), I test the external validity of these results around the world.

I study market timing hypothesis for 33 countries that are listed in Table A2. Jensen, Kelly, and Pedersen (2022)[3] documents international evidence for the return predictability of anomaly characteristics. Motivated by this predictability, I extend my method and create a mispricing score for each international firm using 144 continuous anomaly characteristics in their dataset.

I start my sample construction by including all the stocks between 1990 and 2019. My sample starts in 1990 because SDC has very limited coverage for non-U.S. shares in that period (McLean, Zhang, and Zhao (2011)). Then, I apply suggested screening by Jensen, Kelly, and Pedersen (2022) such as including only common stocks that are listed in the main exchanges, main observations, and primary listings. I obtain anomaly characteristics, along with market variables such as return, industry, and split-adjusted number of shares outstanding from this dataset. To remove the potential biases from low number of observations, I removed each country cross section that has fewer than 100 observations. I also exclude the countries that have fewer than 50 SEO or share repurchases in the full sample period. The construction of mispricing score is identical to the mispricing score constructed for the U.S. sample and explained in detail in Section 2.2.

I use SDC dataset to obtain SEO sample and use the quarterly difference in split-adjusted shares to identify share repurchases, i.e., a decrease in split-adjusted shares represents a share repurchase. International sample has a similar frequency of SEOs. 0.98% of the total observations has an SEO in a given quarter. However, only 2.17% of the total observations has a share repurchase in a given quarter, which is much lower than the U.S. sample.

Similar to the main analysis for the U.S. firms, I estimate the relation between mispricing and two firm decision variables as represented in Equation (8). The first firm decision variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if

[3]https://jkpfactors.com/

there is no SEO or share repurchase. The second firm decision variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. The firm level control variables are same as in Equation (1) and explained in detail in the Appendix B. I include Country × Industry × Quarter fixed effects instead of including Industry × Quarter fixed effects to also control for any unobservable variation across countries. I cluster my standard errors at Country × Year level. I report the estimated coefficients and associated standard errors in Panel A of Table 8 for both SEOs and share repurchases.

$$\text{Firm Decision}_{i,t+1} = \beta_0 + \beta_1 \times \text{Mispricing Score}_{it} + \text{Controls}_{it} + \gamma_{jkt} + \epsilon_{it} \tag{8}$$

The coefficient of Mispricing Score in each regression confirms that executives are more likely to issue (repurchase) shares when the firm is overvalued (undervalued) in the stock market. This result is statistically significant at 1% level. The economic significance of the relation between mispricing and SEO/repurchase decision is lower than the US sample but still sizable. A one standard deviation increase (decrease) in mispricing score leads to a 7.5% (16.6%) increase in the likelihood of SEOs (share repurchases) relative to the unconditional mean. These findings show that market timing strategies are not limited to the U.S. firms and are confirmed when I use a large set of countries as a sample.

I further investigate whether there is any difference in using market timing strategies across countries. I argue that investor protection should have an effect on the relation between mispricing and corporate finance decisions. This argument is motivated by McLean, Pontiff, and Watanabe (2009), who find that the return predictability of ISSUE variable, changes in shares outstanding, is higher in countries with stronger investor protection. If investor protection is low, investors would be reluctant to participate in SEOs or sell shares when a firm announces a share repurchase. For example, investors would be willing to participate in an SEO in a high investor protection country but be afraid of doing so in a very low investor protection country because the cost of information asymmetry would be very large for them. In that case, since there will be no counter party for firms in a stock trade, executives can not use market timing strategies. This is not the case for high investor protection countries since market timing strategies are not fully revealing.

I use World Bank's "Strength of investor protection" data[4] for 33 countries in my sample and augment Equation (8) by including a "High Investor Protection" indicator variable that is equal to 1 if a country is above median in terms of investor protection for a given year and 0 otherwise. I also interact "High Investor Protection" variable with "Mispricing Score" to observe the effect of mispricing on firm decision for countries with different levels of investor protection. Investor protection data is available for the sample period between 2008-2018, therefore my sample period includes the firm-quarter observations in this period. The estimated model is as follows:

$$\begin{aligned} \text{Firm Decision}_{i,t+1} &= \beta_0 + \beta_1 \times \text{High Investor Protection} + \beta_2 \times \text{Mispricing Score} \\ &+ \beta_3 \times \text{Mispricing Score}_{it} \times \text{High Investor Protection} + \text{Controls}_{it} + \gamma_{jkt} + \epsilon_{it} \end{aligned} \tag{9}$$

I report the estimated coefficients and standard errors in Panel B of Table 8. My estimation results show that the documented evidence for market timing in Panel A is fully driven by the countries with high investor protection. The estimated coefficient of "Mispricing Score" is statistically insignificant for both SEOs and share repurchases, documenting that firms in low investor protection countries do not respond to mispricing in their SEO and share repurchase decisions. These results highlight the importance of country level characteristics in market timing and confirm my hypothesis that market timing is more likely to exist in high investor protection countries.

[4] https://govdata360.worldbank.org

6 Robustness Tests

6.1 Orthogonalized Mispricing Measure

In Section 2.2, I discuss the potential drawbacks of using existing mispricing measures to test market timing hypothesis. However, it is still useful to show that the mispricing measure I use is different than the existing measures. To isolate and characterize the novel feature of my measure, I orthogonalize my mispricing measure with respect to the existing measures. I obtain orthogonalized mispricing score by regressing my mispricing measure on each of the existing measures separately, and then obtaining the residual series from each regression. Existing mispricing measures include Book to Market ratio (BM), Past 12-month net of market return (Past Return), Residual Income Model (RIM), and Mutual Fund buy pressure (Buy Pressure) and explained below:

BM: Total book value of equity divided by market capitalization, calculated as market price of the stock times total shares outstanding

Past Return: Buy and hold stock return minus value weighted CRSP market return in the past 12 months.

RIM: Total book value of equity plus discounted value of analyst forecasts of future earnings.

Buy Pressure: Overvalued stocks are those heavily purchased by mutual funds with large capital inflows, but not subject to widespread buying pressure by other mutual funds.

I estimate Equation(1) by using each orthogonalized mispricing measure. I argue that my mispricing score explains the SEO/repurchase decision even after removing the effects of the existing mispricing measures. In Table 9, I report estimated coefficients and associated standard errors of each orthogonalized Mispricing Score. First four columns represent the models including an orthogonalized mispricing score with respect to an existing measure. The parenthesis next to "Mispricing Score" denotes which variable I use as an existing measure to estimate orthogonalized version of my mispricing score. I also orthogonalize my mispricing measure with respect to all of the existing measures together and include Orthogonalized Mispricing Score (All) in the model. I report the estimated coefficient of Orthogonalized Mispricing Score (All) in the last column of each panel. In each specification in Panel A, the dependent variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. In Panel B, the dependent variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase.

The estimated coefficients of "Orthogonalized Mispricing Score" in each panel confirm that my mispricing measure explains SEO and share repurchase decisions even after removing the effect of the existing measures, supporting the novel feature of my measure. Moreover, the magnitude of the estimated coefficient of each orthogonalized versions of my mispricing score is comparable to that of mispricing score reported in Table 2. My findings show that even orthogonalizing with respect to all of the existing variables do not change the results and the relation between mispricing score and SEO/repurchase decision remains both statistically and economically significant. These results confirm that my mispricing measure has more explanatory power in explaining SEO/repurchase decision and this relation can not be explained by the existing mispricing measures that are used to test market timing hypothesis.

6.1.1 The Relation Between Mispricing Score and SEO/Repurchase Decision by Market Capitalization

In the previous sections, I show evidence that executives use market timing strategies. However, there might be a potential concern that the total effect of these results on the economy would be limited if only the executives of small firms are using market timing strategies. This concern can be due to two reasons. First, large firm executives would incur higher reputation costs if they use market timing strategies since market timing leads to wealth loss for new shareholders in SEOs and for short term shareholders in share repurchases. Second, arbitrageurs would allocate less attention to the small firms, thereby leading to any mispricing lasts longer for small firms. Although I use market capitalization as a firm level control, small firms would still affect the estimation results if a high fraction of small firm executives use market timing strategies.

To alleviate this concern, I sort stocks into terciles on market capitalization at the beginning of each quarter and then estimate Equation (1) for the firms in each tercile separately. I report estimation results in Table 10. Panel A reports the coefficients when the "Firm Decision" variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. I document that the effect of mispricing score on SEO decision is smallest for the smallest stocks, and largest for the largest stocks. A one standard deviation increase in mispricing score makes the largest firms 1.04% more likely to issue shares, and the result is statistically significant at 1% level.

Panel B reports the coefficients when the "Firm Decision" variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. I document that the effect of mispricing score on share repurchase decision is smallest for the smallest stocks, and largest for the largest stocks. A one standard deviation increase in mispricing score makes the largest firms 5.33% more likely to repurchase shares, and the result is statistically significant at 1% level. These findings show that the sensitivity of executives to mispricing score in SEO/repurchase decisions is not fully driven by small firms, therefore impacts a large portion of the total economy.

6.2 Controlling for Unvested Shares

When I study the effect of mispricing on SEO/repurchase decision for different levels of executive equity ownership, I only include vested shares and options to the calculation. Since unvested shares have not been earned yet, their effect on the executives' incentives would be limited. However, if managers own unvested shares and plan to stay in the firm for a long period, then unvested shares might also create an incentive for market timing.

To investigate the robustness of my previous results to taking unvested shares into account, I first calculate unvested stock to total compensation ratio and sort firms into terciles at the beginning of each quarter. Then, I include tercile dummy variables as additional control variables in Equation (7). This analysis answers the question that controlling for executives' total unvested shares, how much existing equity ownership affects firm's SEO/repurchase decision. I report the estimation results in Panel A of Table 11. Moreover, I also create a new executive ownership variable that combines vested and unvested equity ownership as a measure of total executive ownership to examine the total incentives. I report these results in Panel B of Table 11.

I find that controlling for unvested shares, managers who own more equity in the firm are still more sensitive to the mispricing in SEO and share repurchase decisions. The estimated coefficients are comparable to the ones in Table 6 and retain statistical significance at 1% level. I also find that the combined executive ownership variable that includes both vested and unvested shares still explains SEO and share repurchase decisions, and the economic effect is comparable in each model with 1% statistical significance.

7 Conclusion

Stock prices can not always reflect fundamental value and firm executives would identify the times when the stock price deviates from the fundamental value. Market timing hypothesis claims that firm executives can maximize long term shareholder value by issuing equity when the firm is overvalued and repurchase shares when the firm is undervalued.

The challenge to test the market timing hypothesis is to identify mispriced (overvalued and undervalued) stocks. Past studies use both ex-ante and ex-post measures of mispricing. However, there is still a debate on using these variables as a measure of mispricing in testing market timing hypothesis. Moreover, more recent papers that propose new mispricing measures to solve this issue are also debated, therefore we do not have a conclusive result yet.

To contribute to market timing literature, I create a mispricing measure by using 155 anomaly characteristics that predict future returns. I test the market timing hypothesis using this mispricing measure and document that executives are more likely to issue (repurchase) equity when the equity is overvalued (undervalued) in the stock market. I also show that the explanatory power of mispricing score becomes larger if I only include anomalies that are published after the sample date. This finding confirms that anomalies that are likely to represent stronger mispricing have more explanatory power in SEO/repurchase decisions and further supports market timing hypothesis.

I also document that when executives own more equity in the firm, they are more sensitive to mispricing in their SEO and share repurchase decisions because they would gain more personal benefits from market timing. To further gain confidence in my findings regarding market timing, I test whether executives time the market in mergers and acquisitions. I find that executives use equity as currency in M&A transactions when the stock is overvalued and cash when the stock is undervalued. Finally, I also document international evidence for market timing by studying 33 countries. The economic significance for international evidence is still sizable and related to investor protection in a country. Overall, these findings support the market timing hypothesis for an international sample and show external validity of the market timing hypothesis.

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Table 1: Mispricing Score vs Future Returns

At the beginning of each month between January 1980 and December 2019, I sort stocks into quintile portfolios based on mispricing score that is constructed using 155 anomaly characteristics. The construction of mispricing score is explained in detail in Section 2.2. I report estimated coefficients and associated standard errors from regressing quintile portfolio returns on Fama French 3 factors. Portfolio returns are calculated as the value weighted average of stock returns within each portfolio. Last column reports the results when the dependent variable is spread portfolio return, which is the return difference between the first quintile portfolio (”Undervalued”) and last quintile portfolio (”Overvalued”). Significance levels are denoted by *, **, *** for 10%, 5%, and 1% levels respectively.

	Undervalued	2	3	4	Overvalued	Spread
Mkt	0.91***	1.00***	1.09***	1.06***	0.93***	-0.02
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)
SMB	-0.05***	-0.08***	0.08***	0.28***	0.40***	-0.45***
	(0.02)	(0.01)	(0.02)	(0.03)	(0.04)	(0.04)
HML	0.18***	0.05***	-0.14***	-0.15***	-0.30***	0.48***
	(0.02)	(0.01)	(0.02)	(0.03)	(0.04)	(0.05)
Constant	0.21***	0.01	-0.31***	-0.35***	-0.55***	0.76***
	(0.05)	(0.04)	(0.06)	(0.09)	(0.10)	(0.13)
Observations	480	480	480	480	480	480

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2: The Relation Between Mispricing Score and Financial Decisions of Firms

Panel A of this table reports linear probability estimates of the relation between mispricing score and seasoned equity offering (SEO) decision (Column 1), between mispricing score and shares issued to total shares outstanding ratio (Column 2), between mispricing score and employee-initiated issuances, and between mispricing score and total fees (gross spread) paid to the underwriters of the SEO (Column 4). Mispricing score is constructed using 155 anomaly characteristics and explained in detail in Section 2.2. In Column 1, the dependent variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. In Column 2, I replace the dependent variable with $\log(1+\frac{\text{shares issued}}{\text{shares outstanding}})$ value. In Column 3, the dependent variable is an employee-initiated issuance indicator that is equal to 1 if number of shares outstanding increases less than 2% and 0 if number of shares outstanding remains the same. Each specification includes industry×quarter fixed effects along with firm level characteristics that are documented in Appendix B. In Column 4, the dependent variable is logarithm of total gross spread paid to the underwriters of the SEO. Panel B of this table reports linear probability estimates of the relation between mispricing score and share repurchase decision (Column 1) and the relation between mispricing score and shares repurchased to total shares outstanding ratio (Column 2). In Column 1, the dependent variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. In Column 2, I replace the dependent variable with $\log(1+\frac{\text{shares repurchased}}{\text{shares outstanding}})$ value. Each specification includes industry×quarter fixed effects along with firm level characteristics. Standard errors are clustered at year level and the significance levels are denoted by *, **, *** for 10%, 5%, and 1% levels respectively.

(a) SEOs

	SEO	Shares Issued/Shrout	Employee Initiated Issuances (Δ Shrout<2%)	Gross Spread
Mispricing Score	0.73***	0.15***	-0.28	6.39***
	(0.06)	(0.01)	(0.37)	(0.75)
% change in DV from -s/2 to +s/2 of Mispricing Score relative to unconditonal (%)	58.8	15.6		6.6
Industry × Quarter FE	✓	✓	✓	
Controls	✓	✓	✓	
Observations	440,357	440,357	378,907	6,906
Adjusted R^2	0.02	0.01	0.28	0.02

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Share Repurchases

	Repurchase	Shares Repurchased/Shrout
Mispricing Score	-4.07***	-0.09***
	(0.38)	(0.01)
% change in DV from +s/2 to -s/2 of Mispricing Score relative to unconditonal (%)	27.9	9.6
Industry × Quarter FE	✓	✓
Controls	✓	✓
Observations	495,503	495,503
Adjusted R^2	0.08	0.01

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Decomposing Mispricing Score by Publication Date of the Anomalies

This table represents the linear probability model (with industry by quarter fixed effects) estimates of the relation between SEO (Panel A) or share repurchase (Panel B) decision and two different anomaly based mispricing scores. The dependent variable in Panel A is SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. The dependent variable in Panel B is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. The first mispricing score uses the anomalies that are published in the academic journals after the sample date (Unpublished) and the second mispricing score uses the anomalies that are published in the academic journals before the sample date (Published). The construction of each mispricing score is explained in detail in Section 3.1.2. The first two columns report the associated coefficients and standard errors when each mispricing score is included in the model one at a time. The last column reports the associated coefficients and standard errors when both mispricing scores are included in the model. I test the equality of the coefficients for the two mispricing scores and report the associated χ^2 and p-values at the bottom of the last column. Each specification includes industry×quarter fixed effects along with firm level characteristics that are documented in Appendix B. Standard errors are clustered at year level and the significance levels are denoted by *, **, *** for 10%, 5%, and 1% levels respectively.

(a) SEOs

	SEO	SEO	SEO
Mispricing Score (Published)	0.26***		0.10*
	(0.06)		(0.05)
Mispricing Score (Unpublished)		0.51***	0.49***
		(0.09)	(0.09)
Industry × Quarter FE	✓	✓	✓
Controls	✓	✓	✓
Observations	440,357	418,390	418,390
Adjusted R^2	0.02	0.02	0.02
χ^2(β_Misp. Score (Unpub.) = β_Misp Score (Pub.))			8.72
p-value			0.01

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Share Repurchases

	Repurchase	Repurchase	Repurchase
Mispricing Score (Published)	-2.66***		-1.48***
	(0.62)		(0.49)
Mispricing Score (Unpublished)		-3.23***	-2.92***
		(0.36)	(0.33)
Industry × Quarter FE	✓	✓	✓
Controls	✓	✓	✓
Observations	495,503	465,899	465,899
Adjusted R^2	0.07	0.07	0.07
χ^2(β_Misp. Score (Unpub.) = β_Misp Score (Pub.))			4.26
p-value			0.05

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Decomposing Published Anomalies

This table represents the linear probability model (with industry by quarter fixed effects) estimates of the relation between SEO (Panel A) or share repurchase (Panel B) decision and three different anomaly based mispricing scores. The dependent variable in Panel A is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. The dependent variable in Panel B is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. The first mispricing score uses the anomalies that are published in the academic journals after the sample date (Mispricing Score (Unpublished)), second mispricing score uses the anomalies that are published in the academic journals within 10 years before the sample date ($MispricingScore(Published < 10years)$), and the third mispricing score uses the anomalies that are published in the academic journals at least 10 years before the sample date ($MispricingScore(Published >= 10years)$). The construction of each mispricing score is explained in detail in Section 3.1.3. The first three columns report the associated coefficients and standard errors when each mispricing score is included in the model one at a time. The last column reports the associated coefficients and standard errors when all of the mispricing scores are included in the model. I test the equality of the coefficients for the Mispricing Score (Unpublished) and Mispricing Score (Published<10 years), and Mispricing Score (Published<10 years) and Mispricing Score (Published>=10 years). I report the associated χ^2 and p-values at the bottom of the last column. Each specification includes industry×quarter fixed effects along with firm level characteristics that are documented in Appendix B. Standard errors are clustered at year level and the significance levels are denoted by *, **, *** for 10%, 5%, and 1% levels respectively.

(a) SEOs

	SEO	SEO	SEO	SEO
Mispricing Score (Unpublished)	0.43***			0.45***
	(0.07)			(0.09)
Mispricing Score (Published<10 years)		0.18***		0.15**
		(0.04)		(0.06)
Mispricing Score (Published>=10 years)			0.05	0.00
			(0.05)	(0.04)
Industry × Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	418,390	440,357	408,322	386,355
Adjusted R^2	0.02	0.02	0.02	0.02
$\chi^2(\beta_{\text{Misp. Score Unpub.}} = \beta_{\text{Misp Score Pub<10 yrs}})$				5.18
p-value				0.03
$\chi^2(\beta_{\text{Misp Score Pub<10 yrs}} = \beta_{\text{Misp Score Pub>=10 yrs}})$				4.70
p-value				0.04

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Share Repurchases

	Repurchase	Repurchase	Repurchase	Repurchase
Mispricing Score (Unpublished)	-3.08***			-2.74***
	(0.32)			(0.30)
Mispricing Score (Published<10 years)		-2.36***		-1.51***
		(0.51)		(0.45)
Mispricing Score (Published>=10 years)			-0.37	0.02
			(0.23)	(0.17)
Industry × Quarter FE	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Observations	465,899	495,503	481,270	451,666
Adjusted R^2	0.07	0.07	0.07	0.07
$\chi^2(\beta_{\text{Misp. Score Unpub.}} = \beta_{\text{Misp Score Pub<10 yrs}})$				3.66
p-value				0.06
$\chi^2(\beta_{\text{Misp Score Pub<10 yrs}} = \beta_{\text{Misp Score Pub>=10 yrs}})$				12.94
p-value				0.00

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Decomposing Mispricing Score by Accounting Anomalies vs Other Anomalies

This table represents the linear probability model (with industry by quarter fixed effects) estimates of the relation between SEO (Panel A) or share repurchase (Panel B) decision and two different anomaly based mispricing scores. The dependent variable in Panel A is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. The dependent variable in Panel B is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. The first mispricing score uses the anomalies that are classified as "Accounting" anomalies based on Chen and Zimmermann's (2021) classification and the second mispricing score uses other anomalies. The construction of each mispricing score is explained in detail in Section 3.1.4. The first two columns report the associated coefficients and standard errors when each mispricing score is included in the model one at a time. The last column reports the associated coefficients and standard errors when both mispricing scores are included in the model. I test the equality of the coefficients for the two mispricing scores and report the associated χ^2 and p-values at the bottom of the last column. Each specification includes industry×quarter fixed effects along with firm level characteristics that are documented in Appendix B. Standard errors are clustered at year level and the significance levels are denoted by *, **, *** for 10%, 5%, and 1% levels respectively.

(a) SEOs

	SEO	SEO	SEO
Mispricing Score (Accounting)	0.71***		0.72***
	(0.05)		(0.05)
Mispricing Score (Others)		0.30***	-0.04
		(0.05)	(0.04)
Industry × Quarter FE	✓	✓	✓
Controls	✓	✓	✓
Observations	440,357	440,357	440,357
Adjusted R^2	0.02	0.02	0.02
χ^2(β_Misp. Score (Account.) = β_Misp Score Pub (Others))			117.15
p-value			0.00

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Share Repurchases

	Repurchases	Repurchases	Repurchases
Mispricing Score (Accounting)	-3.72***		-3.50***
	(0.34)		(0.33)
Mispricing Score (Others)		-2.29***	-0.65***
		(0.28)	(0.23)
Industry × Quarter FE	✓	✓	✓
Controls	✓	✓	✓
Observations	495,503	495,503	495,503
Adjusted R^2	0.08	0.07	0.08
χ^2(β_Misp. Score (Account.) = β_Misp Score Pub (Others))			51.83
p-value			0.00

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: The Effect of Executives' Equity Ownership on the Relation Between Mispricing Score and SEO/Repurchase Decision

This table represents the linear probability model (with industry by quarter fixed effects) estimates of the relation between mispricing score and SEO/ share repurchase decision depending on the executives' equity ownership in the firm. Mispricing score is constructed using 155 anomaly characteristics and explained in detail in Section 2.2. In each panel, Column 1 represents the estimated results from the model where the dependent variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. Column 2 represents the estimated results from the model where the dependent variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. Panel A reports the estimated relation between mispricing score and SEO/repurchase decision depending on the CEO ownership to total compensation ratio and Panel B reports the estimated relation between mispricing score and SEO/repurchase decision depending on the equally weighted average of all executive ownership to total compensation ratios. Executive ownership includes vested equity and options when available. If option ownership is missing due data availability, I only use equity ownership. Total compensation is the total payments to the executive in the previous fiscal year. After calculating the ownership by compensation ratios, I split firms into terciles based on the value of these ratios at the beginning of each quarter. I add tercile indicator variables along with the interaction of these variables with the mispricing score. Each specification includes industry×quarter fixed effects along with firm level characteristics that are documented in Appendix B. Standard errors are clustered at year level and the significance levels are denoted by *, **, *** for 10%, 5%, and 1% levels respectively.

(a) Only CEOs

	SEO	Repurchase
Mispricing Score	0.78***	-5.80***
	(0.10)	(0.41)
Equity Ownership Tercile=3 × Mispricing Score	0.08	-2.00***
	(0.15)	(0.27)
Equity Ownership Tercile=3 × Mispricing Score	0.43***	-1.89***
	(0.11)	(0.40)
Industry × Quarter FE	✓	✓
Controls	✓	✓
Observations	84,109	116,499
Adjusted R^2	0.03	0.13

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) All Executives

	SEO	Repurchase
Mispricing Score	0.56***	-4.21***
	(0.08)	(0.37)
Equity Ownership Tercile=3 × Mispricing Score	0.19*	-1.83***
	(0.10)	(0.36)
Equity Ownership Tercile=3 × Mispricing Score	0.42***	-2.38***
	(0.10)	(0.42)
Industry × Quarter FE	✓	✓
Controls	✓	✓
Observations	91,541	128,670
Adjusted R^2	0.03	0.12

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Market Timing in Mergers and Acquisitions

This table reports linear probability estimates of the relation between mispricing score and mergers and acquisitions activity. I split mergers and acquisitions into two groups by the payment method. In the first column, I report estimated coefficients of mispricing score when dependent variable is equal to 1 if acquiring firm uses equity as a payment method and 0 otherwise. In the second column, I report estimated coefficients of mispricing score when dependent variable is equal to 1 if acquiring firm uses cash as a payment method and 0 otherwise. Mispricing score is constructed using 155 anomaly characteristics and explained in detail in Section 2.2. Each specification includes industry×year fixed effects along with firm level characteristics that are documented in Appendix B. Standard errors are clustered at year level and the significance levels are denoted by *, **, *** for 10%, 5%, and 1% levels respectively.

	Payment Method	
	Stock Only	Cash Only
Mispricing Score	0.08***	-0.03**
	(0.02)	(0.01)
% change in DV from -s/2 to +s/2 of Mispricing Score relative to unconditonal (%)	34.2	-9.8
Industry × Year FE	✓	✓
Controls	✓	✓
Observations	529,869	529,869
Adjusted R^2	0.00	0.01
Coefficient: Mispricing Score		
$\chi^2(\beta_{StockOnly} = \beta_{Cashonly})$	37.96	
p-value	0.00	

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: International Evidence

This table reports linear probability estimates of the relation between mispricing score and seasoned equity offering (SEO) decision (Column 1), and between mispricing score and share repurchase (Column 2) decision for a sample of firms from 33 countries. The construction of mispricing score is identical to the mispricing score constructed for the US sample and explained in detail in Section 2.2. I obtain the anomaly variables and stock characteristics from Jensen, Kelly, and Pedersen (Forthcoming). I only include countries that have at least 50 SEOs or share repurchases and exclude the cross-section of firms that have fewer than 100 firms for a given country. In Column 1, I report the estimated results when the dependent variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. In Column 2, I report the estimated results when the dependent variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. Each specification includes country×industry×quarter fixed effects along with firm level characteristics that are documented in Appendix B. Standard errors are clustered at country×year level and the significance levels are denoted by *, **, *** for 10%, 5%, and 1% levels respectively.

(a) All Firms

	SEO	Repurchase
Mispricing Score	0.07**	-0.36***
	(0.04)	(0.07)
% change in DV from -s/2 to +s/2 of Mispricing Score relative to unconditonal (%)	7.5	16.6
Industry × Country × Quarter FE	✓	✓
Controls	✓	✓
Observations	1,721,974	1,721,974
Adjusted R^2	0.01	0.04

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) The Effect of Investor Protection on Market Timing

	SEO	Repurchase
Mispricing Score	-0.07	-0.02
	(0.07)	(0.06)
High Investor Protection Country × Mispricing Score	0.30***	-0.42***
	(0.08)	(0.15)
Industry × Country × Quarter FE	✓	✓
Controls	✓	✓
Observations	866,313	866,313
Adjusted R^2	0.01	0.04

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Orthogonalized Mispricing Measure

This table reports linear probability estimates of the relation between orthogonalized versions of mispricing score and SEO (Panel A) or share repurchase decision (Panel B). Each orthogonalized mispricing score is constructed by regressing the anomaly based mispricing score, explained in detail in Section 2.2, on the existing measures of mispricing separately and then taking the residual series from this regression. I explain each orthogonalized mispricing scores in Section 6.1. In the first four columns of each panel, I report estimated results when I include each orthogonalized mispricing score in the model. Finally, I regress anomaly based mispricing score on the existing mispricing measures together and create "Orthogonalized Mispricing Score (All)" variable using the residual series from this regression. In the last column, I report estimated results when I include "Orthogonalized Mispricing Score (All)" in the model. In each specification in Panel A, the dependent variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. In Panel B, the dependent variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. Each specification includes industry×quarter fixed effects along with firm level characteristics that are documented in Appendix B. Standard errors are clustered at year level and the significance levels are denoted by *, **, *** for 10%, 5%, and 1% levels respectively.

(a) SEOs

	SEO	SEO	SEO	SEO	SEO
Orthogonalized Mispricing Score (BM)	0.78***				
	(0.05)				
Orthogonalized Mispricing Score (Past Return)		0.75***			
		(0.05)			
Orthogonalized Mispricing Score (RIM)			0.69***		
			(0.10)		
Orthogonalized Mispricing Score (Buy Pressure)				0.62***	
				(0.06)	
Orthogonalized Mispricing Score (All)					1.00***
					(0.11)
Industry × Quarter FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Observations	527,017	527,017	37,474	151,443	27,683
Adjusted R^2	0.02	0.02	0.02	0.02	0.03

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Share Repurchases

	Repurchase	Repurchase	Repurchase	Repurchase	Repurchase
Orthogonalized Mispricing Score (BM)	-4.41***				
	(0.35)				
Orthogonalized Mispricing Score (Past Return)		-4.13***			
		(0.36)			
Orthogonalized Mispricing Score (RIM)			-5.71***		
			(0.47)		
Orthogonalized Mispricing Score (Buy Pressure)				-5.05***	
				(0.34)	
Orthogonalized Mispricing Score (All)					-6.98***
					(0.53)
Industry × Quarter FE	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Observations	499,448	499,448	37,428	150,052	27,662
Adjusted R^2	0.08	0.08	0.17	0.13	0.17

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: The Relation Between Mispricing Score and SEO/Repurchase Decision by Market Capitalization

Panel A of this table reports linear probability estimates of the relation between mispricing score and seasoned equity offering (SEO) decision. Each column represents the estimated results for small, medium, and large firms separately. Mispricing score is constructed using 155 anomaly characteristics and explained in detail in Section 2.2. In each column, the dependent variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. To identify small, medium, and large firms, I first calculate firm size by multiplying share price with number of shares outstanding at the beginning of each quarter. Then, I sort firms into tercile portfolios based on firm size. Panel B of this table reports linear probability estimates of the relation between mispricing score and share repurchase decision. Each column represents the estimated results for small, medium, and large firms separately. In each column, the dependent variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. Each specification includes industry×quarter fixed effects along with firm level characteristics that are documented in Appendix B. Standard errors are clustered at year level and the significance levels are denoted by *, **, *** for 10%, 5%, and 1% levels respectively.

(a) SEOs

	Small	2	Large
Mispricing Score	0.21***	0.78***	1.04***
	(0.04)	(0.07)	(0.09)
Industry × Quarter FE	✓	✓	✓
Controls	✓	✓	✓
Observations	149,241	147,023	143,031
Adjusted R^2	0.01	0.02	0.03

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Share Repurchases

	Small	2	Large
Mispricing Score	-2.27***	-3.49***	-5.33***
	(0.21)	(0.32)	(0.53)
Industry × Quarter FE	✓	✓	✓
Controls	✓	✓	✓
Observations	158,283	162,531	173,839
Adjusted R^2	0.03	0.05	0.13

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: The Effect of Executives' Unvested Equity Ownership on the Relation Between Mispricing Score and SEO/Repurchase Decision

This table represents the linear probability model (with industry by quarter fixed effects) estimates of the relation between mispricing score and SEO/ share repurchase decision depending on the executives' equity ownership in the firm by taking unvested shares into account. Mispricing score is constructed using 155 anomaly characteristics and explained in detail in Section 2.2. In each panel, Column 1 represents the estimated results from the model where the dependent variable is an SEO indicator that is equal to 1 if there is an SEO in a quarter for stock i, and 0 if there is no SEO or share repurchase. Column 2 represents the estimated results from the model where the dependent variable is a share repurchase indicator that is equal to 1 if there is a share repurchase in a quarter for stock i, and 0 if there is no SEO or share repurchase. Panel A reports the estimated relation between mispricing score and SEO/repurchase decision depending on the CEO's ownership in the firm to total compensation ratio. CEO's Ownership includes vested equity and options when available. If option ownership is missing due data availability, I only use equity ownership. Total compensation is the total payments to the executive in the previous fiscal year. After calculating the ownership by compensation ratios, I split firms into terciles based on the value of these ratios at the beginning of each quarter. I add tercile indicator variables along with the interaction of these variables with the mispricing score. Each specification includes industry×quarter fixed effects along with firm level characteristics that are documented in Appendix B. In addition to these controls, I also control for the ownership of unvested shares. I add a control variable that is the ratio of total value of unvested shares to the CEO compensation. In Panel B, instead of adding unvested share ownership as a control variable, I define ownership in the firm as a sum of vested and unvested equity and options. Standard errors are clustered at year level and the significance levels are denoted by *, **, *** for 10%, 5%, and 1% levels respectively.

(a) Equity Ownership and SEO & Repurchase Decision

	SEO	Repurchase
Mispricing Score	0.82***	-9.50***
	(0.09)	(0.39)
Equity Ownership = 2 × Mispricing Score	0.05	-2.39***
	(0.10)	(0.40)
Equity Ownership = 3 × Mispricing Score	0.30***	-2.61***
	(0.10)	(0.37)
Firm Controls	Yes	Yes
CEO Controls (Unvested Shares)	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

(b) Equity Ownership and SEO & Repurchase Decision

	SEO	Repurchase
Mispricing Score	0.83***	-9.73***
	(0.09)	(0.37)
Equity Ownership (Vested+Unvested) = 2 × Mispricing Score	0.01	-1.98***
	(0.10)	(0.41)
Equity Ownership (Vested+Unvested) = 3 × Mispricing Score	0.32***	-2.37***
	(0.10)	(0.37)
Firm Controls	Yes	Yes

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Appendix

A Tables

Table A1: List of Anomalies that are Used to Calculate Mispricing Score

This table documents the stock market anomalies used in constructing mispricing score.

Acronym	Long Description	Paper	Journal	Category
Abnormalaccruals	Abnormal Accruals	Xie (2001)	AR	Accounting
Accruals	Accruals	Sloan (1996)	AR	Accounting
Activism1	Takeover vulnerability	Cremers and Nair (2005)	JF	13F
Activism2	Active shareholders	Cremers and Nair (2005)	JF	13F
Adexp	Advertising Expense	Chan, Lakonishok and Sougiannis (2001)	JF	Accounting
Ageipo	IPO and age	Ritter (1991)	JF	Event
Am	Total assets to market	Fama and French (1992)	JF	Accounting
Analystrevision	EPS forecast revision	Hawkins, Chamberlin, Daniel (1984)	FAJ	Analyst
Analystvalue	Analyst Value	Frankel and Lee (1998)	JAE	Analyst
Announcementreturn	Earnings announcement return	Chan, Jegadeesh and Lakonishok (1996)	JF	Price
Aop	Analyst Optimism	Frankel and Lee (1998)	JAE	Analyst
Beta	CAPM beta	Fama and MacBeth (1973)	JPE	Price
Betafp	Frazzini-Pedersen Beta	Frazzini and Pedersen (2014)	JFE	Price
Betaliquidityps	Pastor-Stambaugh liquidity beta	Pastor and Stambaugh (2003)	JPE	Price
Betatailrisk	Tail risk beta	Kelly and Jiang (2014)	RFS	Price
Betavix	Systematic volatility	Ang et al. (2006)	JF	Price
Bidaskspread	Bid-ask spread	Amihud and Mendelsohn (1986)	JFE	Trading
Brandinvest	Brand capital investment	Belo, Lin and Vitorino (2014)	RED	Accounting
Cashprod	Cash Productivity	Chandrashekar and Rao (2009)	WP	Accounting
Cboperprof	Cash-based operating profitability	Ball et al. (2016)	JFE	Accounting
Cf	Cash flow to market	Lakonishok, Shleifer, Vishny (1994)	JF	Accounting

(continued)

Table A1: List of Anomalies that are Used to Calculate Mispricing Score (Cont.)

Acronym	**Long Description**	**Paper**	**Journal**	**Category**
Cfp	Operating Cash flows to price	Desai, Rajgopal, Venkatachalam (2004)	AR	Accounting
Changeinrecommendation	Change in recommendation	Jegadeesh et al. (2004)	JF	Analyst
Chassetturnover	Change in Asset Turnover	Soliman (2008)	AR	Accounting
Cheq	Growth in book equity	Lockwood and Prombutr (2010)	JFR	Accounting
Chinv	Inventory Growth	Thomas and Zhang (2002)	RAS	Accounting
Chinvia	Change in capital inv (ind adj)	Abarbanell and Bushee (1998)	AR	Accounting
Chnncoa	Change in Net Noncurrent Op Assets	Soliman (2008)	AR	Accounting
Chnwc	Change in Net Working Capital	Soliman (2008)	AR	Accounting
Chtax	Change in Taxes	Thomas and Zhang (2011)	JAR	Accounting
Compequiss	Composite equity issuance	Daniel and Titman (2006)	JF	Accounting
Compositedebtissuance	Composite debt issuance	Lyandres, Sun and Zhang (2008)	RFS	Accounting
Coskewacx	Coskewness using daily returns	Ang, Chen and Xing (2006)	RFS	Price
Coskewness	Coskewness	Harvey and Siddique (2000)	JF	Price
Customermomentum	Customer momentum	Cohen and Frazzini (2008)	JF	Other
Delbreadth	Breadth of ownership	Chen, Hong and Stein (2002)	JFE	13F
Delcoa	Change in current operating assets	Richardson et al. (2005)	JAE	Accounting
Delcol	Change in current operating liabilities	Richardson et al. (2005)	JAE	Accounting
Deldrc	Deferred Revenue	Prakash and Sinha (2012)	CAR	Accounting
Delequ	Change in equity to assets	Richardson et al. (2005)	JAE	Accounting
Delfinl	Change in financial liabilities	Richardson et al. (2005)	JAE	Accounting
Dellti	Change in long-term investment	Richardson et al. (2005)	JAE	Accounting
Delnetfin	Change in net financial assets	Richardson et al. (2005)	JAE	Accounting
Dnoa	change in net operating assets	Hirshleifer, Hou, Teoh, Zhang (2004)	JAE	Accounting
Dolvol	Past trading volume	Brennan, Chordia, Subra (1998)	JFE	Trading
Earningsconsistency	Earnings consistency	Alwathainani (2009)	BAR	Accounting
Earningsforecastdisparity	Long-vs-short EPS forecasts	Da and Warachka (2011)	JFE	Analyst
Earningsstreak	Earnings surprise streak	Loh and Warachka (2012)	MS	Accounting
Earningssurprise	Earnings Surprise	Foster, Olsen and Shevlin (1984)	AR	Analyst

(continued)

Table A1: List of Anomalies that are Used to Calculate Mispricing Score (Cont.)

Acronym	**Long Description**	**Paper**	**Journal**	**Category**
Earnsupbig	Earnings surprise of big firms	Hou (2007)	RFS	Accounting
Ebm	Enterprise component of BM	Penman, Richardson and Tuna (2007)	JAR	Accounting
Entmult	Enterprise Multiple	Loughran and Wellman (2011)	JFQA	Accounting
Ep	Earnings-to-Price Ratio	Basu (1977)	JF	Price
Equityduration	Equity Duration	Dechow, Sloan and Soliman (2004)	RAS	Price
Exclexp	Excluded Expenses	Doyle, Lundholm and Soliman (2003)	RAS	Analyst
Feps	Analyst earnings per share	Cen, Wei, and Zhang (2006)	WP	Analyst
Fgr5Yrlag	Long-term EPS forecast	La Porta (1996)	JF	Analyst
Firmage	Firm age based on CRSP	Barry and Brown (1984)	JFE	Other
Firmagemom	Firm Age - Momentum	Zhang (2004)	JF	Price
Forecastdispersion	EPS Forecast Dispersion	Diether, Malloy and Scherbina (2002)	JF	Analyst
Fr	Pension Funding Status	Franzoni and Marin (2006)	JF	Accounting
Frontier	Efficient frontier index	Nguyen and Swanson (2009)	JFQA	Accounting
Gp	gross profits / total assets	Novy-Marx (2013)	JFE	Accounting
Gradexp	Growth in advertising expenses	Lou (2014)	RFS	Accounting
Grcapx	Change in capex (two years)	Anderson and Garcia-Feijoo (2006)	JF	Accounting
Grcapx3Y	Change in capex (three years)	Anderson and Garcia-Feijoo (2006)	JF	Accounting
Grltnoa	Growth in long term operating assets	Fairfield, Whisenant and Yohn (2003)	AR	Accounting
Grsaletogrinv	Sales growth over inventory growth	Abarbanell and Bushee (1998)	AR	Accounting
Grsaletogroverhead	Sales growth over overhead growth	Abarbanell and Bushee (1998)	AR	Accounting
Herf	Industry concentration (sales)	Hou and Robinson (2006)	JF	Other
Herfasset	Industry concentration (assets)	Hou and Robinson (2006)	JF	Other
Herfbe	Industry concentration (equity)	Hou and Robinson (2006)	JF	Other
High52	52 week high	George and Hwang (2004)	JF	Price
Hire	Employment growth	Bazdresch, Belo and Lin (2014)	JPE	Other
Idiovol3F	Idiosyncratic risk (3 factor)	Ang et al. (2006)	JF	Price
Idiovolaht	Idiosyncratic risk (AHT)	Ali, Hwang, and Trombley (2003)	JFE	Price
Illiquidity	Amihud's illiquidity	Amihud (2002)	JFM	Trading

(continued)

Table A1: List of Anomalies that are Used to Calculate Mispricing Score (Cont.)

Acronym	**Long Description**	**Paper**	**Journal**	**Category**
Indmom	Industry Momentum	Grinblatt and Moskowitz (1999)	JFE	Price
Indretbig	Industry return of big firms	Hou (2007)	RFS	Price
Intanbm	Intangible return using BM	Daniel and Titman (2006)	JF	Accounting
Intancfp	Intangible return using CFtoP	Daniel and Titman (2006)	JF	Accounting
Intanep	Intangible return using EP	Daniel and Titman (2006)	JF	Accounting
Intansp	Intangible return using Sale2P	Daniel and Titman (2006)	JF	Accounting
Intmom	Intermediate Momentum	Novy-Marx (2012)	JFE	Price
Investment	Investment to revenue	Titman, Wei and Xie (2004)	JFQA	Accounting
Investppeinv	change in ppe and inv/assets	Lyandres, Sun and Zhang (2008)	RFS	Accounting
Invgrowth	Inventory Growth	Belo and Lin (2012)	RFS	Accounting
Io_Shortinterest	Inst own among high short interest	Asquith Pathak and Ritter (2005)	JFE	13F
Lrreversal	Long-run reversal	De Bondt and Thaler (1985)	JF	Price
Maxret	Maximum return over month	Bali, Cakici, and Whitelaw (2010)	JF	Price
Meanrankrevgrowth	Revenue Growth Rank	Lakonishok, Shleifer, Vishny (1994)	JF	Accounting
Mom12M	Momentum (12 month)	Jegadeesh and Titman (1993)	JF	Price
Mom12Moffseason	Momentum without the seasonal part	Heston and Sadka (2008)	JFE	Price
Mom6M	Momentum (6 month)	Jegadeesh and Titman (1993)	JF	Price
Mom6Mjunk	Junk Stock Momentum	Avramov et al (2007)	JF	Price
Momoffseason	Off season long-term reversal	Heston and Sadka (2008)	JFE	Price
Momoffseason06Yrplus	Off season reversal years 6 to 10	Heston and Sadka (2008)	JFE	Price
Momoffseason11Yrplus	Off season reversal years 11 to 15	Heston and Sadka (2008)	JFE	Price
Momoffseason16Yrplus	Off season reversal years 16 to 20	Heston and Sadka (2008)	JFE	Price
Momseason	Return seasonality years 2 to 5	Heston and Sadka (2008)	JFE	Price
Momseason06Yrplus	Return seasonality years 6 to 10	Heston and Sadka (2008)	JFE	Price
Momseason11Yrplus	Return seasonality years 11 to 15	Heston and Sadka (2008)	JFE	Price
Momseason16Yrplus	Return seasonality years 16 to 20	Heston and Sadka (2008)	JFE	Price
Momseasonshort	Return seasonality last year	Heston and Sadka (2008)	JFE	Price
Mrreversal	Medium-run reversal	De Bondt and Thaler (1985)	JF	Price

(continued)

Table A1: List of Anomalies that are Used to Calculate Mispricing Score (Cont.)

Acronym	**Long Description**	**Paper**	**Journal**	**Category**
Netdebtfinance	Net debt financing	Bradshaw, Richardson, Sloan (2006)	JAE	Accounting
Netdebtprice	Net debt to price	Penman, Richardson and Tuna (2007)	JAR	Accounting
Netequityfinance	Net equity financing	Bradshaw, Richardson, Sloan (2006)	JAE	Accounting
Noa	Net Operating Assets	Hirshleifer et al. (2004)	JAE	Accounting
Numearnincrease	Earnings streak length	Loh and Warachka (2012)	MS	Accounting
Operprof	operating profits / book equity	Fama and French (2006)	JFE	Accounting
Operprofrd	Operating profitability R&D adjusted	Ball et al. (2016)	JFE	Accounting
Opleverage	Operating leverage	Novy-Marx (2010)	ROF	Accounting
Optionvolume1	Option to stock volume	Johnson and So (2012)	JFE	Trading
Optionvolume2	Option volume to average	Johnson and So (2012)	JFE	Trading
Orderbacklog	Order backlog	Rajgopal, Shevlin, Venkatachalam (2003)	RAS	Accounting
Orderbacklogchg	Change in order backlog	Baik and Ahn (2007)	Other	Accounting
Orgcap	Organizational capital	Eisfeldt and Papanikolaou (2013)	JF	Accounting
Pctacc	Percent Operating Accruals	Hafzalla, Lundholm, Van Winkle (2011)	AR	Accounting
Pcttotacc	Percent Total Accruals	Hafzalla, Lundholm, Van Winkle (2011)	AR	Accounting
Predictedfe	Predicted Analyst forecast error	Frankel and Lee (1998)	JAE	Accounting
Pricedelayrsq	Price delay r square	Hou and Moskowitz (2005)	RFS	Price
Pricedelayslope	Price delay coeff	Hou and Moskowitz (2005)	RFS	Price
Pricedelaytstat	Price delay SE adjusted	Hou and Moskowitz (2005)	RFS	Price
Probinformedtrading	Probability of Informed Trading	Easley, Hvidkjaer and O'Hara (2002)	JF	Trading
Ps	Piotroski F-score	Piotroski (2000)	AR	Accounting
Rd	R&D over market cap	Chan, Lakonishok and Sougiannis (2001)	JF	Accounting
Rdability	R&D ability	Cohen, Diether and Malloy (2013)	RFS	Accounting
Rdcap	R&D capital-to-assets	Li (2011)	RFS	Accounting
Rds	Real dirty surplus	Landsman et al. (2011)	AR	Accounting
Realestate	Real estate holdings	Tuzel (2010)	RFS	Accounting
Residualmomentum	Momentum based on FF3 residuals	Blitz, Huij and Martens (2011)	JEmpFin	Price
Retconglomerate	Conglomerate return	Cohen and Lou (2012)	JFE	Price

(continued)

Table A1: List of Anomalies that are Used to Calculate Mispricing Score (Cont.)

Acronym	**Long Description**	**Paper**	**Journal**	**Category**
Returnskew	Return skewness	Bali, Engle and Murray (2015)	Book	Price
Returnskew3F	Idiosyncratic skewness (3F model)	Bali, Engle and Murray (2015)	Book	Price
Rev6	Earnings forecast revisions	Chan, Jegadeesh and Lakonishok (1996)	JF	Analyst
Revenuesurprise	Revenue Surprise	Jegadeesh and Livnat (2006)	JFE	Accounting
Roe	net income / book equity	Haugen and Baker (1996)	JFE	Accounting
Sfe	Earnings Forecast to price	Elgers, Lo and Pfeiffer (2001)	AR	Analyst
Shareiss1Y	Share issuance (1 year)	Pontiff and Woodgate (2008)	JF	Accounting
Shareiss5Y	Share issuance (5 year)	Daniel and Titman (2006)	JF	Accounting
Shortinterest	Short Interest	Dechow et al. (2001)	JFE	Other
Skew1	Volatility smirk near the money	Xing, Zhang and Zhao (2010)	JFQA	Options
Smileslope	Put volatility minus call volatility	Yan (2011)	JFE	Options
Sp	Sales-to-price	Barbee, Mukherji and Raines (1996)	FAJ	Accounting
Std_Turn	Share turnover volatility	Chordia, Subra, Anshuman (2001)	JFE	Trading
Tang	Tangibility	Hahn and Lee (2009)	JF	Accounting
Tax	Taxable income to income	Lev and Nissim (2004)	AR	Accounting
Totalaccruals	Total accruals	Richardson et al. (2005)	JAE	Accounting
Varcf	Cash-flow to price variance	Haugen and Baker (1996)	JFE	Accounting
Volmkt	Volume to market equity	Haugen and Baker (1996)	JFE	Trading
Volsd	Volume Variance	Chordia, Subra, Anshuman (2001)	JFE	Trading
Volumetrend	Volume Trend	Haugen and Baker (1996)	JFE	Trading
Xfin	Net external financing	Bradshaw, Richardson, Sloan (2006)	JAE	Accounting
Zerotrade	Days with zero trades	Liu (2006)	JFE	Trading

Table A2: List of Countries that are Used in the International Analysis

This table documents the list of countries that are used in the international analysis.

Australia	India	Turkey
Belgium	Israel	Vietnam
Brazil	Italy	South Africa
Canada	Japan	
Switzerland	Korea, Republic	
Chile	Malaysia	
China	Netherlands	
Germany	Norway	
Denmark	New Zealand	
Spain	Philippines	
Finland	Poland	
France	Russian Federation	
United Kingdom	Singapore	
Hong Kong SAR, China	Sweden	
Indonesia	Thailand	

B Control Variables

Return on Asset: The most recent annual value of "Operating Income Before Depreciation" (OIBDP) variable scaled by lag "Total Asset" (AT).

Cash by Asset: The most recent quarterly value of "Cash and Cash Equivalents" (CHEQ) variable scaled by "Total Asset" (ATQ). If quarterly value is missing, I replace variable value with the most recent ratio from annual data.

Market Capitalization: The value of stock price multiplied by total shares outstanding at the beginning of quarter .

Leverage: The most recent quarterly value of "Total Liabilities" (LTQ) variable scaled by "Total Asset" (ATQ). If quarterly value is missing, I replace variable value with the most recent ratio from annual data.

Dividend Yield: The most recent annual value of "Dividends" (DVC) variable scaled by end of year market value, calculated as the product of stock price and total shares outstanding.

Volatility: Daily volatility of returns in the previous quarter.

Δ ***Volatility:*** Year over year change in the daily volatility of returns in the previous quarter.

Firm Age: Number of months since first listed in CRSP database.