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Essays on Share Repurchases and Boom-Bust Cycles

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Abstract

My doctoral dissertation consists of three chapters on financial economics. In the first chapter, I examine whether a firm's share repurchases and issuances reveal information on its future 2-year stock returns. Firm-quarter observations with repurchases or issuances are each divided into twenty 5-percentile bins sorted by their magnitude. I regress 2-year future stock returns on the bins and find a non-linear relationship between the change in shares outstanding and returns. Firms making repurchases (issuances) of less than 9.3% (1.4%) of shares outstanding outperform the equal-weight portfolio by 6.4% (3.9%). These observations account for 90% of repurchases and 70% of issuances. Firms making larger repurchases (issuances) underperform by 1.9% (5.1%).

In the second chapter, I examine whether investors could use share repurchases and issuances to create outperforming portfolios from 2003-2019. First, I examine two exchange-traded funds which track repurchasing companies and find no evidence they outperformed. Second, I investigate whether repurchases and issuances of U.S. firms have predictive effects from 2003-2017, and I find large issuances predict lower returns. Finally, I construct a portfolio which short-sells the stocks of firms which make large share issuances and a portfolio which invests in all firms except the large share issuers. I backtest these strategies and find both outperformed the market.

In the third chapter, I show an economy with delegated investment management and assets with correlated tail risk will experience endogenous boom-bust cycles where longer booms lead to larger crashes. I examine a dynamic model populated by savers and investment managers, where savers delegate their wealth to investment managers to invest in a project. Risky projects produce returns that depend on the investment manager's ability. Tail-risk projects produce high average outputs after a good aggregate shock but produce no output after a bad shock. In equilibrium, savers fire managers who generate low returns. Low-ability managers to invest in tail-risk projects to reduce their chance of being fired. As such, the population of low-ability managers increases after good shocks and falls after bad shocks, which produces boom-bust cycles in output where longer booms are followed by larger crashes.

Keywords: long-run abnormal returns, market efficiency, stock repurchases, financial markets and the macroeconomy, financial crises, delegated investment management

Summary for Lay Audience

My doctoral dissertation consists of three chapters on financial economics. My first chapter examines whether a firm's share repurchases and issuances predict the firm's future stock returns over the 1975-2017 period. Share repurchases occur when a firm buys back its shares from the stock market, and share issuances occur when a firm issues new shares on the stock market. I find that firms making repurchases (issuances) of less than 9.3% (1.4%) of its previous shares outstanding over 3 months have higher returns of 6.4% (3.9%) over the following 2 years, compared to firms which did not make repurchases or issuances. These observations account for 90% of repurchases and 75% of issuances. Firms making larger repurchases (issuances) underperform by 1.9% (5.1%).

In the second chapter, I examine whether investors can use share repurchase and issuance information to create portfolios which outperform the market. First, I examine two exchange-traded funds which track the returns of repurchasing companies and find no evidence they outperformed the market. Second, I investigate whether repurchases and issuances of U.S. firms have predictive effects in the 2003-2017 period, and find large issuances predict lower returns. Finally, I construct two portfolio which use the information from large issuances and show they outperformed the market from 2003-2019.

In the third chapter, I show that if assets with correlated tail risk exist, investment management can cause boom-bust cycles where longer booms lead to larger crashes. These tail-risk assets generate higher average returns than other assets most of the time, but there is a small chance that all tail-risk assets generate no returns and lose their value. Investment managers with less ability to generate high returns prefer to invest in assets with tail risk to improve their chances of attracting and retaining clients. When the tail risk event does not occur, the number of lower-ability investment managers and the amount invested in assets with tail risk increase . As such, the amount invested in assets with tail risk and the losses that would occur in a crash increase with a longer period of stability.

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Chapter 1

Repurchases, Issuances, and Stock Returns

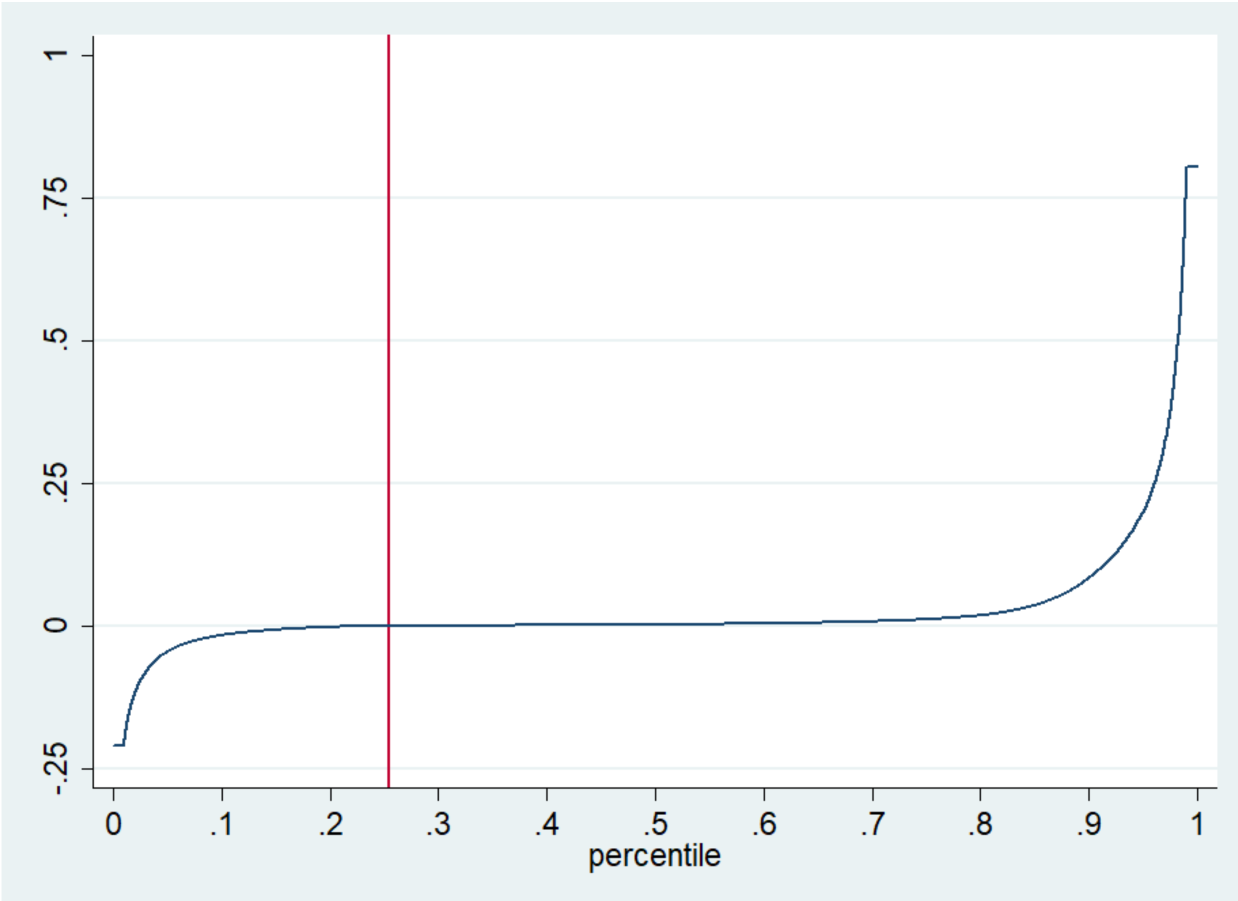
1.1 Introduction

The academic literature has generally found firms that repurchase their shares have higher future returns and firms who issue shares have lower future returns (e.g. Pontiff and Woodgate (2008), Lakonishok and Vermaelen (1990), Loughran and Ritter (1995)). Their findings motivated the creation of funds which track the performance of firms that make large stock repurchases.[1] However, these studies have not explored whether there is a non-linear relationship between the percent of shares repurchased or issued and the firm's future returns. For example, a small issuance may represent employees of the firm exercising stock options, while a large issuance may reflect the need to raise new equity. These activities could provide different information about the long-run stock returns that can't be captured in a linear model.

In this paper, I examine whether the magnitude of a firm's changes in shares outstanding predicts its long-run stock returns. I use data from the CRSP and Compustat databases from 1975-2017 to construct measures of a firm's share repurchase and issuance using its one-quarter percent change in shares outstanding. Most one-quarter changes in shares outstanding are less than

[1] The Invesco Buyback Achievers ETF track US firms who reduced their shares outstanding by 5% over the past 12 months, and the SPDR S&P 500 Buyback ETF tracks the 100 firms in the S&P 500 index with the largest stock buyback ratios in the past 12 months.

Figure 1.1: CDF of 1-quarter changes in shares outstanding, 1975-2017



Notes: This graphs the CDF of the one-quarter percent change in shares outstanding, adjusted to remove effects of stock splits. This graph does not include firm-quarter observations with no change in shares outstanding, which represents 37% of the total sample. Changes in shares outstanding are winsorized at the 1st and 99th percentiles.

1%, but a small fraction of changes are much larger (see Figure 1.1).

These differences raise the possibility that the relationship between changes in shares outstanding and stock returns could be non-linear. I sort firm-quarter observations with repurchases into 5-percentile bins based on their magnitudes to capture potential non-linearity in the effect of changes in shares outstanding on returns. Observations with issuances are similarly sorted into 5-percentile bins. I regress two-year excess stock returns in excess of the CRSP equal-weight portfolio on indicator variables for these bins, controlling for firm characteristics.

I find firms which make small repurchases and issuances outperform firms who make large repurchases and issuances by over 8% over a two-year horizon. Firms making repurchases (issuances) of less than 9.3% (1.4%) of shares outstanding outperform the equal-weight portfolio by 6.4% (3.9%). These observations represent 90% of repurchases and 70% of issuances. Firms making larger repurchases (issuances) underperform by 1.9% (5.1%). These findings are largely robust when they are estimated separately for size and book-to-market quintiles.

Due to the large number of bins, the binned regression has lower power and the results are difficult to summarize. I create two models with fewer variables that can capture the non-linear relationship documented by the binned regression. The first specification uses a polynomial in repurchases and issuances, and the second uses indicator variables for large and small repurchases and issuances. I further confirm the results are robust to cross-sectional dependence using Fama-MacBeth (1973) cross-sectional regressions. The main findings hold with both of these specifications. The predicted effect of large repurchases becomes insignificant, but firms that make small repurchases and issuances still experience higher future returns, and firms that make large issuances still experience lower future returns.

These results differ from the effects of small issuances and large repurchases implied by previous studies. To illustrate these differences, I compare my main findings to the results of a linear specification on changes in shares outstanding and firm controls, similar to the specification used by Pontiff and Woodgate (2008). The linear specification incorrectly predicts the wrong sign for firms who make small issuances and no effect for firms who make small repurchases. For example, the linear specification predicts a firm which increases its shares outstanding by 1% to have lower returns of -0.23%, and a firm that reduces its shares outstanding by 1% would be predicted to have higher returns of 0.23%. In contrast, the polynomial specification predicts the issuing firm would outperform by 1.7% and the repurchasing firm would outperform by 4.3%.

Similarly, a specification which only conditions on whether a repurchase or issuance occurred and not on the magnitude of the repurchase or issuance also produces misleading results. This specification correctly predicts the positive effect of small repurchases but incorrectly predicts that large repurchases would have the same positive effect. This specification would also predict issuances have no significant effect on returns since it averages the positive effect of small issuances with the negative effect of large issuances.

Finally, I examine whether the estimates are robust to different time periods. Fu and Huang (2016) find the stock return effects following changes in shares outstanding are significantly smaller, and the effects of announced repurchases and issuances disappears in the post-2003 period. While I find the effect of small repurchases decreases by roughly a third, none of the coefficients change by a statistically significant amount and the estimated coefficients for small and large issuances in the 2003-2017 subsample are similar to the full sample estimates. I further find the use of one-quarter change in shares outstanding instead of the one-year change used by Fu and Huang (2016) mitigates the decrease in the estimates of small repurchases and issuances.

Previous papers generally find share repurchases predict higher returns in the 1- to 5-year time horizon, while issuances predict lower returns. Daniel and Titman (2006) uses 1968-2003 data and find a negative relationship between the five-year changes in log shares outstanding and monthly stock returns. Pontiff and Woodgate (2008) repeat this with one-year changes in shares outstanding on longer investment horizons in the 1970-2003 sample. They find net share issuances also predict lower returns in the 6-month to 3-year investment horizons. This result holds even when excluding changes in shares outstanding relating to announced repurchase or senior equity offering events. While these papers consider the effect of the size of changes in shares outstanding on stock returns, both restrict this to a linear relationship. I find these linear models produce misleading relationships between changes in shares outstanding and returns.

Most studies in this literature examine the returns of firms announcing share repurchases or issuances. Ikenberry et al. (1995) forms portfolios of firms sorted by size and book-to-market ratios which announced share repurchases from 1980-1990. They compare the returns of these portfolios to those of benchmark portfolios. The portfolios of firms which announced a share repurchase had positive abnormal returns in the 12- to 48-month investment horizons. Peyer and Vermaelen (2009) control for the market return, size, and book-to-market Fama-French (1993) factors and find positive abnormal returns also exist in the 1991-2001 time period. Jagannathan and Stephens (2003) compares the stock returns of frequent versus infrequent repurchasers. Infrequent repurchasers tend to announce larger share repurchases as a fraction of shares outstanding compared to frequent repurchasers (7.7% vs. 6.7% of shares outstanding). They find the operating income of infrequent repurchasers declines more than those of frequent repurchasers following a share repurchase announcement, but do not find conclusive evidence that announcements by frequent and infrequent repurchasers are followed by different future stock returns in the 1- to 3-year horizons. These papers do not directly control for the size of the repurchases. I find while most firms who repurchase shares experience higher returns, the firms who make large repurchases experience average or lower returns.

Loughran and Ritter (1995) and Spiess and Affleck-Graves (1995) examine the returns of firms who announce senior equity offerings (SEOs) from 1970-1990 and 1975-1989, respectively. They match firms who announce an SEO with control firms based on firm characteristics. They find firms which announce SEOs underperform matched firms in the 3-year and 5-year investment horizons. Loughran and Ritter do not control for the size of issuances. Spiess and Affleck-Graves find their results are robust to controlling for the quintiles of gross issuance proceeds or pre-issuance market capitalization, but do not control for the percent change in shares outstanding or market capitalization. I find when controlling for the percent change in shares outstanding, firms who make small issuances outperform while firms who make large issuances underperform.

More recently, Fu and Huang (2016) shows the previously-found effects of repurchase and issuance announcements are smaller in the 2003-2013 period. They find the effect of repurchase and issuance announcements becomes insignificant. While the coefficient on the one-year change in shares outstanding is still significant and negative, they find it shrinks by roughly two-thirds in this period. Similar to Pontiff and Woodgate (2008), their specification is linear in the change in shares outstanding, and they use one-year changes in shares outstanding. I find using 1-quarter changes in shares outstanding, there are no significant differences between coefficients in the full sample and in the post-2003 subsample.

The key variables are defined and their summary statistics are discussed in Section 1.2. The binned regressions are conducted in Section 1.3, and the Fama-Macbeth cross-sectional regressions are conducted in Section 1.4. In Section 1.5, I further control for firm characteristics using size and book-to-market portfolios. Section 1.6 examines whether the effect of repurchases and issuances changed in the 2003-2017 subsample. I confirm the results are robust when using buy-and-hold returns, 1-year changes in shares outstanding, and lagging the predictor variables in Section 1.7. Section 1.8 concludes.

1.2 Data and Summary Statistics

The sample contains firms in the CRSP and Compustat databases from 1975-2017. Firms must be in both databases and observations must have non-missing price and shares outstanding data to be included in the sample. To calculate backward- and forward-looking variables such as 2-year future stock returns, data is collected from 1970-2019. The first 3 quarters and the last 2 quarters of each firm are excluded from the sample to remove entry and exit effects. Observations for which a 3-month change in shares outstanding cannot be calculated are dropped. In total, there are 834,951 firm-quarter observations across 22,137 firms in this sample.

The panel uses a quarterly time unit. This matches the minimum reporting period of the shares outstanding variables from CRSP, which is updated using quarterly and annual financial reports. Other variables which only use data from CRSP, including the holding period return and change in shares outstanding variables, are constructed using monthly data. To construct the quarterly data panel, each quarterly observation from Compustat is matched to the observation from CRSP using the last month of the reporting period.

1.2.1 Key Variables

In this section, the stock return and share repurchase and issuance variables used in this analysis are defined. Stock return and share repurchase and issuance variables are constructed using monthly data, and the time steps referenced in the equations below are months.

Stock Return. The main response variable is two-year cumulative returns, calculated using

1-month holding returns from CRSP.

$$Return_{i,t+1,t+24} = \sum_{\tau=t+1}^{t+24} (MonthlyReturn_{i,\tau}) \tag{1.1}$$

The cumulative return is the sum of the monthly returns for two years. This represents the return after investing a constant dollar value in the stock at the beginning of each month and selling the stock at the end of each month for 2 years, excluding transaction costs. The cumulative returns metric is different from the return an investor receives from buying and holding the stock for 2 years (the buy-and-hold returns), and it can take on values less than -1. Despite these drawbacks, cumulative returns are used over buy-and-hold returns to avoid econometric concerns raised by Fama (1998).[2] The positive skewness of long-run buy-and-hold returns can overstate the significance of the estimated coefficients and using cumulative returns avoids this concern. The use of cumulative returns instead of buy-and-hold returns does not qualitatively affect the results (see Section 1.7.1).

The data contains firms with missing returns in the middle of their samples and firms which exit the sample. To include these observations, missing returns are replaced with the return of the CRSP equal-weighted portfolio for that month, following Pontiff and Woodgate (2008).[3]

Change in Shares Outstanding. I use CRSP data on shares outstanding to calculate the change in shares outstanding, repurchase, and issuance variables. To remove the effect of stock splits, shares outstanding are divided by the cumulative factor to adjust shares:

$$AdjShares_{i,t} = SharesOutstanding_{i,t} / CFacShares_{i,t} \tag{1.2}$$

The change in shares outstanding is defined as the percent change in adjusted shares over the past

[2]Use of cumulative returns is common in the return predictability literature. Ikenberry et al. (1995), Peyer and Vermaelen (2009), and Fu and Huang (2016) examine abnormal returns using both the cumulative and buy-and-hold measures.

[3]These missing returns are usually the result of firms exiting the sample, possibly due to being acquired or bankruptcy. Excluding these firms could bias the estimated results as delistings may be correlated with earlier share repurchases or issuances, and the direction of the bias would not be clear since different reasons for delisting would affect the firm's pre-delisting returns in different directions.

3 months.

$$\%\Delta Shares_{i,t} = \frac{AdjShares_{i,t} - AdjShares_{i,t-3}}{AdjShares_{i,t-3}} \tag{1.3}$$

Observations with a missing change in shares outstanding are dropped. Only 105 observations had missing repurchase values.

The three-month horizon for constructing the change in share outstanding variable is used for three reasons. First, 3 months is the minimum reporting horizon for CRSP data on shares outstanding since it is updated based on quarterly financial reports. Second, a shorter time horizon compared to 1-year metrics used in previous studies (e.g., Pontiff and Woodgate (2008)) means the variable corresponds better with the timing of the repurchase or issuance. Finally, it limits the persistence in the shares outstanding variable, which reduces the risk of understating standard errors.

I define repurchases as 3-month reductions in shares outstanding and issuances as 3-month increases in shares outstanding.

$$Repurchase_{i,t} = \begin{cases} -\%\Delta Shares_{i,t} & \text{if } \%\Delta Shares_{i,t} < 0 \\ 0 & \text{if } \%\Delta Shares_{i,t} \geq 0 \end{cases} \tag{1.4}$$

$$Issuance_{i,t} = \begin{cases} \%\Delta Shares_{i,t} & \text{if } \%\Delta Shares_{i,t} > 0 \\ 0 & \text{if } \%\Delta Shares_{i,t} \leq 0 \end{cases} \tag{1.5}$$

These variables reflect actual changes in shares outstanding and are similar to the change in shares outstanding variables used in Daniel and Titman (2006) and Pontiff and Woodgate (2008). Announcements of share repurchases and issuances are sometimes used in this literature (e.g. Ikenberry et al. (1995)), but these announcements don't necessarily reflect actual share repurchases or issuances. Stephens and Weisbach (1998) find from 1981-1990, only 57% of firms repurchased the targeted number of shares three years after an announcement. Further, 30% of firms repurchased over twice as many shares as targeted. Pontiff and Woodgate (2008) find changes in shares outstanding capture share repurchase and issuance activities beyond announced share repurchases and senior equity offerings. They also find changes in shares outstanding predict future returns even when excluding changes tied to announcements.

Firm controls. I follow Pontiff and Woodgate (2008) and control for firm size, book-to-market ratio, and momentum. These characteristics are commonly used in the literature to predict stock returns. Size is defined as the log of the market capitalization (in millions), book-to-market is defined as the log of the book value of common equity divided by the market capitalization, and momentum is proxied by the prior 6-month buy-and-hold return. More details on the construction of these variables can be found in the appendix.

An indicator variable is created for observations with missing book-to-market values which takes on a value of 1 if the value is missing and 0 otherwise. These missing book-to-market values are set to 0. In total, 145,670 observations representing 17% of the sample had missing book-to-market values. The indicator variable allows these observations to be included in the analysis without affecting the estimated coefficient of the book-to-market variable.

Similar to Pontiff and Woodgate (2008), all variables are winsorized at the 1% and 99% levels to reduce the effect of extreme observations on the analysis.

1.2.2 Summary Statistics

Table 1.1 displays the summary statistics of the variables. The mean 2-year cumulative return is 28%. As expected, this is higher than the mean 2-year S&P 500 return of 20% as the mean cumulative return equally weighs the returns of small firms and large firms.[4] The mean 2-year cumulative return is close to the mean 2-year buy-and-hold return of 28% but has a much smaller skewness at 0.04 compared to 1.79.

The average change in shares outstanding is 0.02 across all firm-quarter observations. This average hides considerable variation in repurchases and issuances. Seventeen percent of the firm-

[4]Studies (e.g. Fama and French (1992)) generally find small firms have higher average returns than large firms. Since the S&P 500 is a value-weighted index, it would apply a smaller weight to the higher average returns of small firms and a larger weight to the lower average returns of large firms.

Table 1.1: Summary statistics, 1975-2017

	Mean	SD	1%	25%	50%	75%	99%	N
Return	0.28	0.69	-1.84	-0.04	0.26	0.61	2.46	834,506
ChangeShares	0.02	0.09	-0.13	0.00	0.00	0.00	0.51	834,506
Repurchases	0.04	0.07	0.00	0.00	0.01	0.03	0.43	137,955
Issuances	0.05	0.14	0.00	0.00	0.00	0.02	1.00	391,310
Size	5.07	2.12	0.61	3.55	4.97	6.50	10.40	834,506
BTM	-0.50	0.95	-3.25	-1.03	-0.47	0.04	2.74	688,836
Momentum	0.07	0.35	-0.69	-0.13	0.04	0.20	1.54	834,506

Notes: This table displays the summary statistics of the variables used in this analysis. Return is the 2-year cumulative stock return: the sum of the monthly holding period returns over the next 24 months. ChangeShares is the one-quarter percent change in shares outstanding. Repurchase is one-quarter percent decreases in shares outstanding and excludes observations with no repurchases. Issuance is one-quarter increases in shares outstanding and excludes observations with no issuances. Size is the log of the market capitalization (in millions). BTM is the book-to-market ratio: the log of the book value of common equity divided by the market capitalization. The BTM statistics exclude observations with missing book-to-market values which comprise 17% of the sample. Momentum is the prior 6-month buy-and-hold return.

quarter observations contained repurchases and 47% contained issuances. As noted in other papers (e.g. Fu and Huang (2016)), repurchases and issuances have grown more common over time. Repurchases and issuances made up only 14% and 42% of the firm-quarter observations from 1975-2002, but grew to 21% and 54% in the 2003-2017 period.

The distributions of repurchases and issuances are both right-skewed (see Table 1.2). Excluding observations with zero repurchases (issuances), the average repurchase (issuance) is 3.5% (5.0%) of shares outstanding. However, over 75% of repurchases and issuances are smaller than the means. The largest 10th percentile of repurchases (issuances) are more than 9 (28) times the size of the medians repurchases (issuances). These large differences in magnitude between the median and the largest repurchases and issuances raise concerns that firms may make large and small repurchases and issuances for different reasons, and that large and small changes in shares outstanding may predict different future stock returns. In this case, a regression model which only includes a slope coefficient for changes in shares outstanding would fail to simultaneously capture the effects of small and large changes in shares outstanding.

Table 1.3 shows the contemporaneous correlation matrix between the main variables. Increases in shares outstanding are correlated with lower 2-year returns. This is consistent with the findings

Table 1.2: Repurchase and issuance centiles (excl. zeroes), 1975-2017

Centile	25	50	75	90	95	99	Mean	SD
Repurchase	0.003	0.010	0.032	0.093	0.167	0.429	0.035	0.070
Issuance	0.001	0.005	0.022	0.130	0.262	1.000	0.050	0.142

Notes: This table displays the centiles of repurchases and issuances. Repurchase is one-quarter percent decreases in shares outstanding. Issuance is one-quarter increases in shares outstanding. Observations with zero repurchases are excluded when calculating repurchase statistics, and observations with zero issuances are excluded when calculating issuance statistics.

Table 1.3: Contemporaneous correlations, 1975-2017

	Return	ChangeShares	Size	BTM	MissBTM
ChangeShares	-0.049				
Size	-0.085	-0.011			
BTM	0.122	-0.057	-0.302		
MissBTM	-0.056	0.065	-0.066	N/A	
Momentum	-0.037	0.032	0.107	-0.216	-0.031

Notes: This table displays the contemporaneous correlations between the main variables. Correlations are calculated including observations with zero change in shares outstanding. Return is the 2-year cumulative stock return: the sum of the monthly holding period returns over the next 24 months. ChangeShares is the one-quarter percent change in shares outstanding. Size is the log of the market capitalization. BTM is the book-to-market ratio: the log of the book value of common equity divided by the market capitalization. The correlations for BTM are calculated excluding observations with missing BTM values. MissBTM is the missing book-to-market indicator variable, which takes on a value of 1 if BTM is missing and is set to 0 otherwise. Momentum is the prior 6-month buy-and-hold return.

in the existing literature (e.g. Pontiff and Woodgate (2008)). Similarly, the correlations of size, book-to-market, and momentum with future returns have the same signs as those found in previous studies on stock returns predictability. Firms with higher returns tend to be smaller firms with high book-to-market ratios (Fama & French, 1992). Stocks that have recently performed well tend to perform worse in the future, while stocks that have recently performed worse tend to perform better in the future (DeBondt & Thaler, 1985).

Table 1.4: Contemporaneous correlations, 1975-2017

	ChangeShares	RepurchIND	IssuanceIND	Repurchase(>0)	Issuance(>0)
Return	-0.049	0.015	-0.038	-0.043	-0.060
Size	-0.011	0.137	0.205	-0.209	-0.112
BTM	-0.057	0.028	-0.207	0.230	0.018
MissBTM	0.065	-0.022	-0.135	0.380	0.234
Momentum	0.032	-0.043	0.057	0.005	0.015

Notes: This table displays the contemporaneous correlations between changes in shares outstanding, repurchase, and issuance variables and the other main variables. Correlations displayed for the Repurchase and Issuance variables are calculated excluding observations with zero repurchases and issuances, respectively. Return is the 2-year cumulative stock return: the sum of the monthly holding period returns over the next 24 months. ChangeShares is the one-quarter percent change in shares outstanding. RepurchIND and IssuanceIND are indicator variables that take on a value of 1 if the observation contained a repurchase or issuance, respectively. Repurchase is one-quarter percent decreases in shares outstanding, and its correlations are calculated using only repurchasing firms. Issuance is one-quarter increases in shares outstanding, and its correlations are calculated using only issuing firms. Size is the log of the market capitalization. BTM is the book-to-market ratio: the log of the book value of common equity divided by the market capitalization. The correlations for BTM are calculated excluding observations with missing BTM values. MissBTM is the missing book-to-market indicator variable, which takes on a value of 1 if BTM is missing and is set to 0 otherwise. Momentum is the prior 6-month buy-and-hold return.

Table 1.4 shows the correlations between returns and firms that repurchase or issue, along with the correlation between returns and the size of the repurchase or issuance conditional on the firm conducting a repurchase or issuance. The correlation between repurchases and returns is not symmetric to the correlation between issuances and returns. Larger issuances are correlated with lower returns, which is consistent with the negative correlation between changes in shares outstanding and returns. However, while firms which make repurchases tend to have higher returns, larger repurchases are also correlated with lower returns. These correlations suggest the relationship between the change in shares outstanding and returns may be non-linear, where small repurchases and issuances may predict future returns differently from large repurchases and issuances.

If share repurchase and issuance plans tend to stretch across quarters, using one-quarter changes in shares outstanding as the explanatory variable may not be appropriate. The one-quarter window would not be able to distinguish between a small one-time repurchase and a large repurchase stretching across several quarters. If the correlations between one-quarter changes in shares outstanding and its lags are large, then a longer window may be appropriate. As shown in Table 1.5, the correlation between the variables and their first lags are all under 6%, and the correlation tends to decrease with the number of lags. This is lower than the autocorrelation of one-year changes in shares outstanding documented by Pontiff and Woodgate (2008) (they find a first-order autocorrelation of 17%). These low autocorrelation values support using a one-quarter window for changes in shares outstanding as they tend to be isolated events.

Table 1.5: Autocorrelation of changes in shares outstanding, 1975-2017

Lags	1	2	3	4	5	6	7	8
ChangeShares	0.057	0.039	0.027	0.030	0.013	0.009	0.011	0.011
Repurchase	0.055	0.047	0.028	0.036	0.013	0.008	0.010	0.030
Issuance	0.060	0.039	0.029	0.033	0.017	0.012	0.015	0.015

Notes: This table displays the autocorrelation function of the change in shares outstanding variables. These correlations are calculated including observations with zero change in shares outstanding, repuchases and issuances. ChangeShares is the one-quarter percent change in shares outstanding. Repurchase is one-quarter percent decreases in shares outstanding. Issuance is one-quarter increases in shares outstanding.

1.3 Regression on Repurchase and Issuance Bins

The finding that larger repurchases and issuances are both correlated with lower returns (see Section 1.2.2) suggests the relationship between changes in shares outstanding and 2-year stock returns may be non-linear. To examine how the magnitude of repurchases and issuances affect predicted stock returns, I regress 2-year excess stock returns on 5-percentile bins of repurchases and issuances, controlling for the firm characteristics.

I find a firm's predicted 2-year excess return depends non-linearly on the magnitude of its shares repurchases and issuances. Firms that make small repurchases and issuances have higher returns compared to firms that do not change their shares outstanding. Firms that make large repurchases and issuances have lower returns. The predicted return doesn't vary significantly with the magnitude of the change in shares outstanding except in the region around the thresholds between small and large repurchases and issuances (9.7% of shares outstanding for repurchases, 1.4% for issuances).

1.3.1 Methodology

I divide observations into bins based on the magnitude of their changes in shares outstanding. Non-zero repurchases and issuances are each sorted into twenty 5-percentile bins by the magnitude of the change in shares outstanding. For each bin, I create an indicator variable which takes on a value of 1 if the repurchase value falls into the associated 5-percentile range and 0 otherwise. Each repurchase bin has roughly 6,898 observations, and each issuance bin has 19,566 observations.[5]

Binning continuous variables reduces the statistical power of the analysis due to the lower variability in the predictor variables and also assumes the predicted effect is constant within bins. Due to the large sample size, the observations with non-zero changes in shares outstanding can be divided into 40 bins with sufficient observations in each bin. The large number of bins smooths out the estimated effect, especially for smaller repurchases and issuances where the 5-percentile bins cover a smaller range.

Controlling for cross-sectional dependence is also a concern. For example, Dittmar and Dittmar (2008) find aggregate repurchases and issuances vary over the business cycle. The estimated coefficients of share repurchases and issuances could capture variation in the average stock return over the business cycle. To partially control for time effects, I use excess cumulative returns as the sum of the monthly excess returns of firm i over the CRSP equal-weight portfolio as the dependent variable:

$$ExReturn_{i,t+1,t+24} = \sum_{\tau=t+1}^{t+24} MonthlyReturn_{i,\tau} - EqualWeightReturn_{\tau}$$

[5]The number of observations in each bin varies slightly due to rounding effects.

The 2-year excess returns variable has a mean of 0.018. Unfortunately, the mean varies across time, which indicates subtracting the market return may not control for all of the cross-sectional dependence within time periods. The mean excess return over the CRSP equal-weight market portfolio is 0.007 in the 1975-1992 period, 0.032 in the 1993-2002 period, and 0.016 in the 2003-2017 period. In Section 1.4, I use Fama-MacBeth cross-sectional regressions on alternative regression specifications to confirm the results from this analysis are robust to time effects.[6]

I run a pooled regression of 2-year excess stock returns on the indicator variables for the repurchase and issuance bins and firm controls. The main variables of interest are the coefficients on the repurchase and issuance bins, β_1 and β_2.

$$ExReturn_{i,t+1,t+24} = \alpha + \beta_1 RepurchaseBins_{i,t} + \beta_2 IssuanceBins_{i,t} + \gamma_1 FirmControls_{i,t} + \epsilon_{i,t} \tag{1.6}$$

Driscoll and Kraay (1998) standard errors are used to account for heteroskedasticity, cross-sectional dependence, and autocorrelation.

1.3.2 Results

The analysis shows the magnitude of repurchases and issuances have a non-linear effect on predicted stock returns (see 1.2). Firms which make small repurchases and issuances outperform compared to firms which do not repurchase or issue their shares. The firms making the smallest 90% of repurchases (less than 9.3% of shares outstanding) have higher excess returns of 6.4% over 2 years. This effect does not vary significantly by the magnitude of the repurchase as long as the magnitude remains smaller than 9.3% of shares outstanding. Similarly, the firms making the 70% smallest issuances (less than 1.4% of shares outstanding) have higher excess returns of 3.9% over two years. Again, these coefficients do not vary significantly with respect to the magnitude of the issuance over this region.

In contrast, firms which make large repurchases and issuances underperform compared to firms

[6] The results are qualitatively and quantitatively similar when including time fixed effects in the regression.

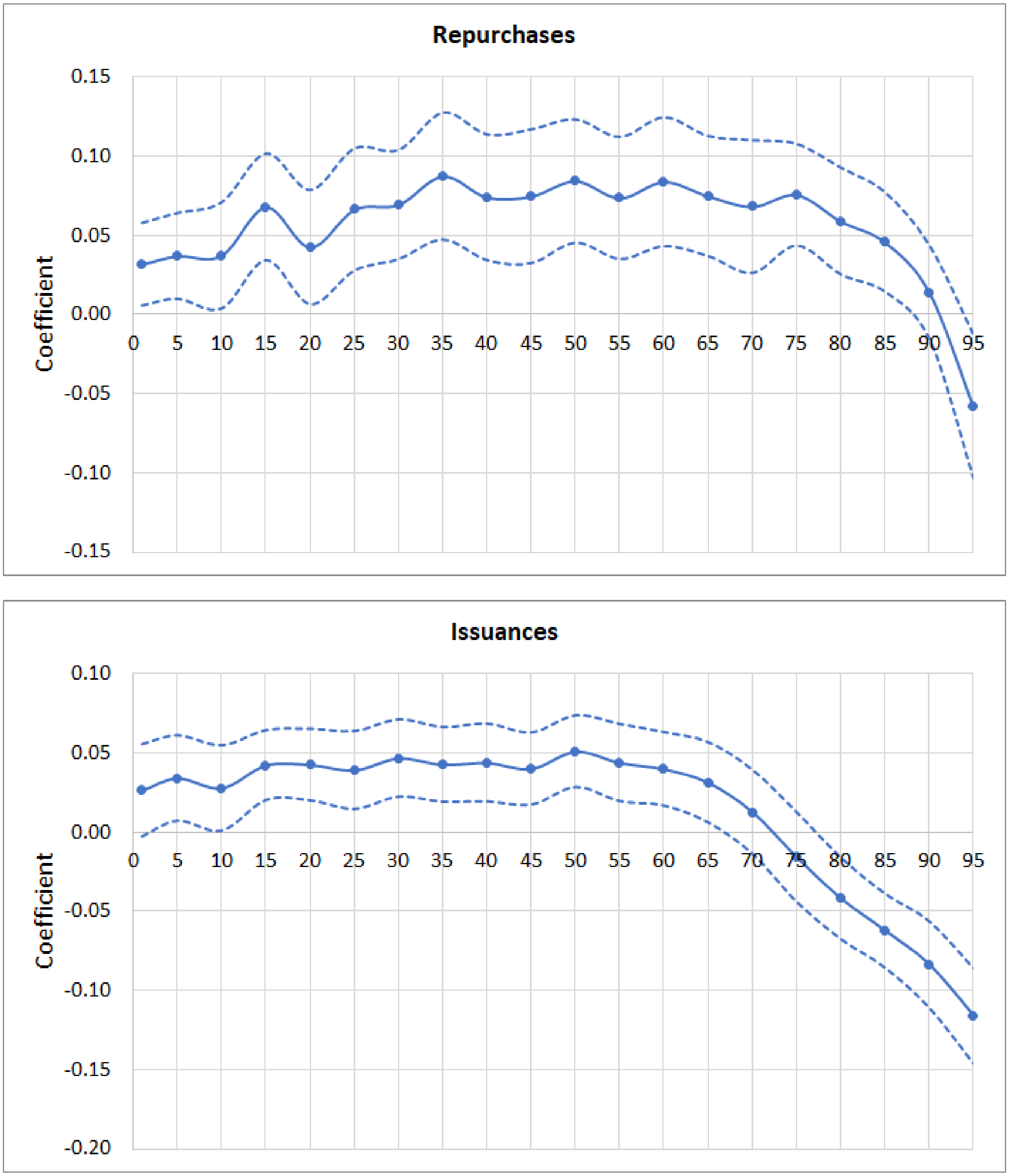
which do not make repurchases or issuances. Firms in the 90th to 95th percentiles of repurchases have average returns, and firms making repurchases larger than the 95th percentile (more than 16.7% of shares outstanding) underperform by -1.9%. Firms making issuances larger than the 70th percentile (more than 1.4% of shares outstanding) underperform by -5.1%.

A linear model of changes in shares outstanding correctly predicts the underperformance of large issuers (see Column 2 of Table 1.6). However, as shown in Figure 1.3, such models cannot capture the outperformance of firms who make small repurchases and issuances or the underperformance of firms who make large repurchases. Most repurchases and issuances are smaller than 1% of shares outstanding, and the coefficient estimated by the linear model predicts a difference in returns of under 0.3% in magnitude. However, firms making these small repurchases and issuances are the firms that significantly outperform the benchmark. The linear model also incorrectly suggests that returns should get larger as repurchases gets larger because it captures the negative effect of large issuances.

A model which only conditions on whether a repurchase or issuance occurred and which does not consider the magnitude of repurchases and issuances correctly predicts the outperformance of small repurchasers, but does not predict the performance of issuers or large repurchasers (see Column 3 of Table 1.6). By averaging the positive effect of small and the negative effect of large issuances, this model incorrectly suggests that issuances do not predict significantly different future returns. Since a large fraction of repurchases are small, it better captures the positive effect of most repurchases but does not capture the negative effect of large repurchases.

These findings suggest previous analyses of the effect of share repurchases and issuances (e.g. Pontiff and Woodgate (2008), Ikenberry et al. (1995), Loughran and Ritter (1995)) may be misspecified. These studies could not distinguish between the effects of large and small repurchases and issuances because they do not consider the magnitude of repurchases and issuances separately.

Figure 1.2: Coefficients on repurchase/issuance bins by percentiles, 1975-2017



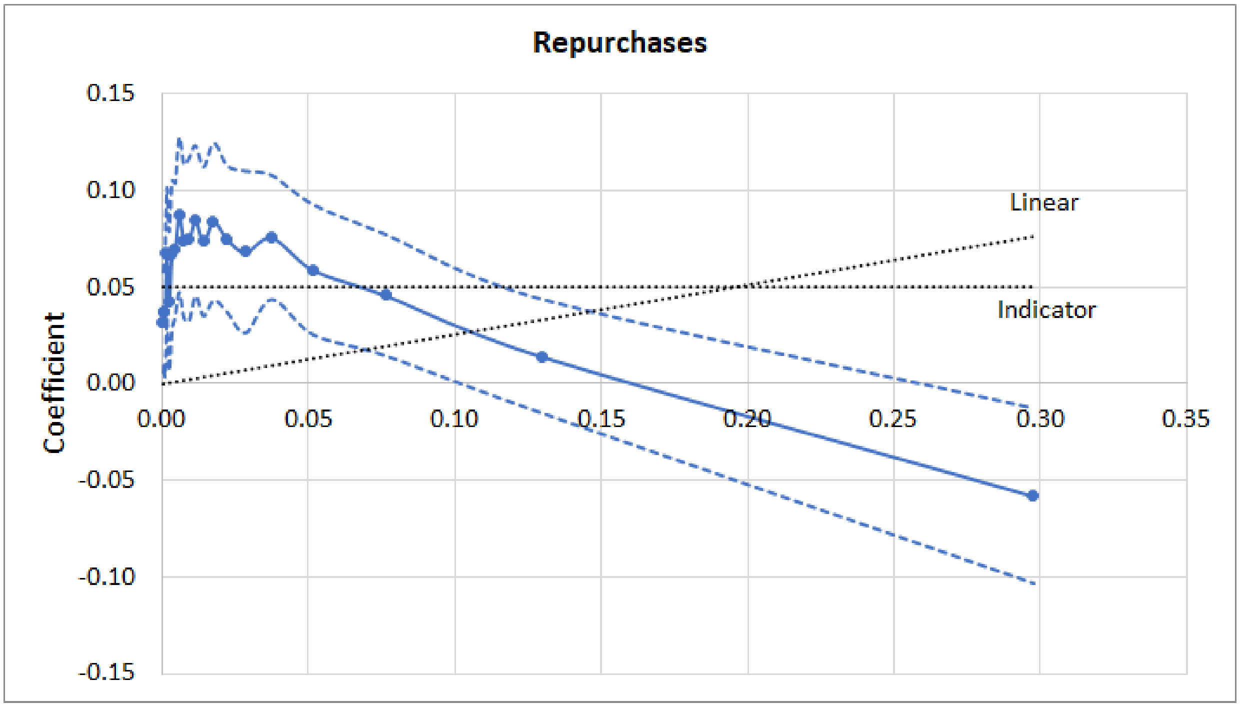
Notes: This figure graphs the coefficients of the indicator variables for the 5-percentile repurchase and issuance bins from the binned regression. The horizontal axis is the percentile of the repurchase or issuance. The plotted points represent the lowest percentile of each 5-percentile bin. The dashed lines represent the 95-percent confidence interval. See Table 1.6 for the coefficients on the control variables.

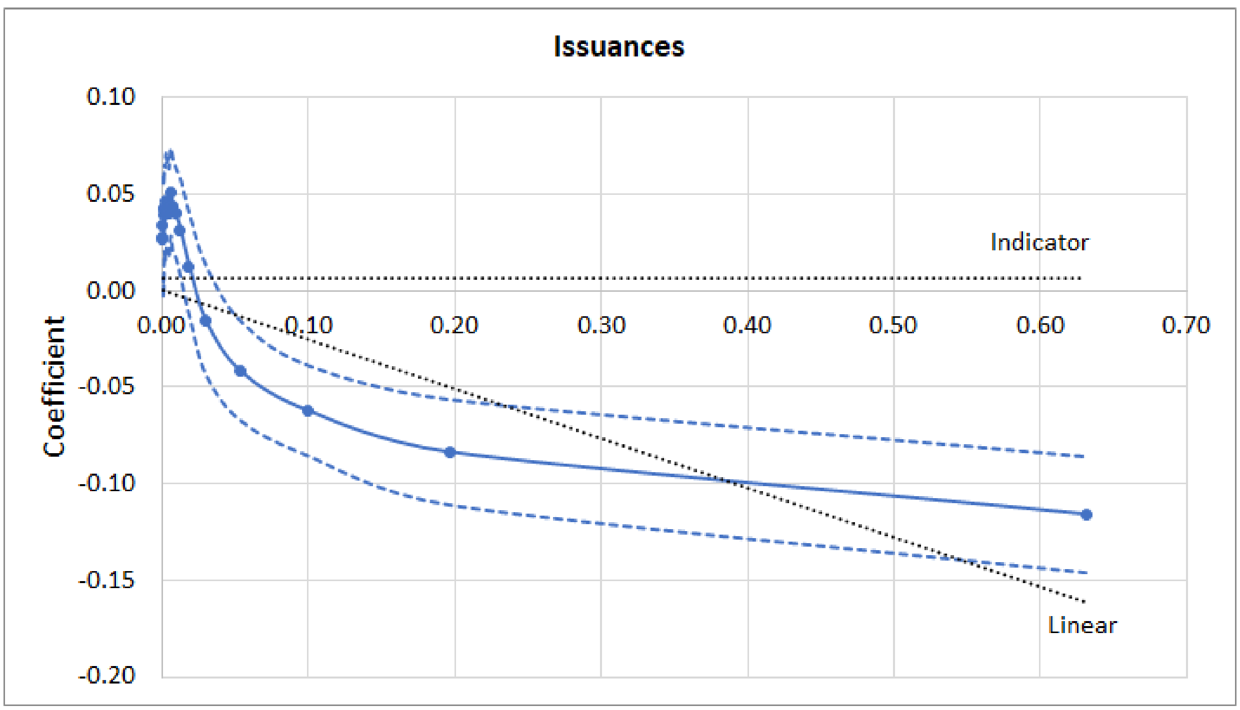
Table 1.6: Coefficients on pooled regressions, 1975-2017

	(1)	(2)	(3)	(4)
ChangeShares		-0.256***		
		(0.0291)		
RepurchaseIND			0.0505***	
			(0.0148)	
IssuanceIND			0.0068	
			(0.0101)	
BinIndicators	YES	NO	NO	NO
Size	-0.0116	-0.0084	-0.0098	-0.0081
	(0.0073)	(0.007)	(0.0072)	(0.007)
BTM	0.0488***	0.0472***	0.0477***	0.0484***
	(0.0133)	(0.0138)	(0.0136)	(0.0139)
MissBTM	-0.0732***	-0.0899***	-0.0926***	-0.0947***
	(0.0183)	(0.0191)	(0.0192)	(0.0192)
Momentum	0.0163	0.0102	0.0105	0.0081
	(0.0196)	(0.0202)	(0.0199)	(0.0202)
Constant	0.0941**	0.0994***	0.0911**	0.0951**
	(0.0367)	(0.037)	(0.0362)	(0.0369)
$R\hat{2}$	0.0106	0.0085	0.0079	0.0072
N	834828	834828	834828	834828

Notes: This table displays the coefficients of the pooled panel regression with Driscoll-Kraay standard errors with the repurchase and issuance bins. See Figure 1.2 or Table A.1 in Appendix A.2 for coefficients on the repurchase and issuance bins. The response variable is the 2-year cumulative stock return: the sum of the monthly holding period returns over the next 24 months. RepurchIND and IssuanceIND are indicator variables that take on a value of 1 if the observation contained a repurchase or issuance, respectively. ChangeShares is the one-quarter percent change in shares outstanding. Size is the log of the market capitalization. BTM is the book-to-market ratio: the log of the book value of common equity divided by the market capitalization. MissBTM is the missing book-to-market indicator variable, which takes on a value of 1 if BTM is missing and is set to 0 otherwise. Momentum is the prior 6-month buy-and-hold return.

Figure 1.3: Coefficients on bins by size of repurchase/issuance, 1975-2017





Notes: This figure graphs the coefficients on the 5-percentile repurchase and issuance bins from the binned regression. The horizontal axis is the fraction of shares outstanding repurchased or issued. The plotted points are the coefficients of the indicator variables for the repurchase and issuance bins, and are graphed at the mid-point fraction of shares outstanding of the range of each 5-percentile bin. The dashed lines represent the 95-percent confidence interval. The dotted line represents the predicted effect using the specification with only the change in shares outstanding. See Column 1 in Table 1.6 for the coefficients on the control variables for the binned regression, and see Column 2 for the coefficients for the specification with the change in shares outstanding.

1.4 Fama-MacBeth Cross-Sectional Regressions

The analysis in Section 1.3 documents a non-linear relationship between changes in shares outstanding and stock returns. However, there is concern that the binned regression does not fully control for time effects. In this section, I follow Pontiff and Woodgate (2008) and use Fama and MacBeth (1973) cross-sectional regressions to control for time effects. Because not all quarters have observations in every repurchase and issuance bin, I use the findings shown in Figure 1.3 to create two specifications which can capture the non-linear relationship between the magnitude of the change in shares outstanding and stock returns. The effect of large repurchases becomes insignificant, but otherwise the previous findings in Section 1.3 are robust.

I again compare the results from these flexible specifications to results from specifications similar to those used in previous studies. A model which only includes a slope coefficient for the change in shares outstanding would incorrectly predict a positive effect for large repurchases and a negligible effect for small repurchases and issuances. A model which only includes indicator variables for whether a repurchase or issuance occurred will correctly predict that most repurchases are followed by higher returns, but incorrectly predicts that issuances are not followed by significantly different returns.

1.4.1 Methodology

I consider two models which can capture the non-linear relationship between changes in shares outstanding and returns described in Section 1.3.2. The first specification allows for a non-linear relationship between returns and changes in shares outstanding using a polynomial on repurchases and issuances.

$$\begin{aligned} Return_{i,t+1,t+24} = \alpha_t + \beta_1 RepurchIND_{i,t} + +\beta_2 Repurchase_{i,t} + \beta_3 Repurchase^2_{i,t} + \\ + \beta_4 IssuanceIND_{i,t} + \beta_5 Issuance_{i,t} + \beta_6 Issuance^2_{i,t} + \gamma_1 FirmControls_{i,t} + \epsilon_{i,t} \end{aligned} \tag{1.7}$$

The coefficients on the indicator variables β_1 and β_4 capture the effects of small repurchases and issuances, while the slope and square term coefficients $\beta_2, \beta_3, \beta_5$ and β_6 capture the effects of large repurchases and issuances.

The second specification uses indicator variables for small and large repurchases and issuances using the thresholds identified in Section 1.3.2:

$$\begin{aligned}
LargeRepurchase_{i,t} &= 1 \text{ if } Repurchase_{i,t} \geq 0.093 \\
SmallRepurchase_{i,t} &= 1 \text{ if } Repurchase_{i,t} \in (0, 0.093) \\
SmallIssuance_{i,t} &= 1 \text{ if } Issuance_{i,t} \in (0, 0.014) \\
LargeIssuance_{i,t} &= 1 \text{ if } Issuance_{i,t} \geq 0.014
\end{aligned}$$

This specification regresses 2-year stock returns on these indicator variables and firm controls:

$$\begin{aligned}
Return_{i,t+1,t+24} =& \alpha_t + \beta_1 LargeRepurchase_{i,t} + \beta_2 SmallRepurchase_{i,t} + \beta_3 SmallIssuance_{i,t} \\
&+ \beta_4 LargeIssuance_{i,t} + \gamma_1 CompanyControls_{i,t} + \epsilon_{i,t}
\end{aligned} \tag{1.8}$$

The importance of controlling for the magnitude of repurchases and issuances non-linearly is highlighted using alternative specifications. The first only considers the change in shares outstanding linearly and does not separate repurchases and issuances variables (similar to the model in Pontiff and Woodgate (2008)). The second only considers indicator variables for repurchases and issuances, and does not consider the size of these repurchases and issuances (similar to models used in Ikenberry et al. (1995) and Loughran and Ritter (1995), although these papers use announcements and not actual repurchases or issuances).

I use the Fama and MacBeth (1973) cross-sectional regressions to control for time effects. A cross-sectional regression is run for each quarter in the sample, and the estimated coefficients are averaged across the time periods. Newey-West (1987) standard errors with a maximum lag of 12 are used to correct for heteroskedasticity and autocorrelation.[7] Petersen (2009) shows Fama-

[7] The results are also robust when using a maximum lag of 36.

MacBeth cross-sectional regressions capture the effects of cross-sectional dependence. Newey-West standard errors captures temporary time-series dependence, although these standard errors may be biased downward in the presence of highly-persistent firm effects.[8]

1.4.2 Results

The effects of small repurchases, small issuances, and large issuances on returns found in Section 1.3.2 are robust to controlling for time fixed effects. Compared to firms which make no repurchases or issuances, firms with small repurchases outperform by 4.3% over 2 years, firms with small issuance outperform by 2.7%, and firms with large issuances underperform by 4.9%. These estimated effects are smaller in magnitude than the coefficients from the binned regression, but they remain statistically significant. The effect of large repurchases becomes insignificant, but it remains significantly different from the effect of small repurchases at the 5% significance level.

Table 1.7 shows the results of the Fama-MacBeth cross-sectional regressions on the specification presented in Equations 1.7 and 1.8, as well as specifications similar to those used by previous studies and ones which decompose changes in shares outstanding into separate slope and intercept terms for repurchases and issuances. Column 1 shows the results of the Fama-Macbeth cross-sectional regressions using Equation 1.7. Firms who make small repurchases and small issuances have higher stock returns, as indicated by the positive and significant coefficients on the repurchase and issuance indicator variables. These are similar to the findings in Section 1.3.2. Firms that make large issuances have lower returns, which are also similar to the findings in Section 1.3.2. The effect of issuances becomes negative at 3.7% of shares outstanding (roughly the 80th percentile); in the binned regressions, the effect of issuances becomes insignificant at the 70th percentile (1.4% of shares outstanding) and turns negative in the 75th percentile (2% of shares outstanding). Unlike in the binned regressions, the predicted effect of large repurchases is insignificant.

[8] Petersen (2009) suggests using two-dimensional clustered standard errors on firms and time to correct for this. I find clustering by quarters produces similarly-sized standard errors. Clustering by year produces larger standard errors. The effect of small issuances becomes insignificant, but its coefficient remains significantly different from that of large issuances.

Table 1.7: Fama-MacBeth regressions, 1975-2017

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
LargeRepurchase		0.006					
		(0.016)					
SmallRepurchase		0.043***					
		(0.009)					
SmallIssuance		0.027***					
		(0.007)					
LargeIssuance		-0.049***					
		(0.010)					
RepurchaseIND	0.043***			0.035***		0.030***	0.044***
	(0.010)			(0.008)		(0.008)	(0.009)
IssuanceIND	0.023***			-0.001		0.012*	0.013**
	(0.007)			(0.006)		(0.01)	(0.007)
ChangeShares			-0.229***			-0.223***	
			(0.03)			(0.027)	
Repurchase	0.021				0.076		-0.139
	(0.160)				(0.0894)		(0.101)
Issuance	-0.635***				-0.203***		-0.211***
	(0.063)				(0.0329)		(0.029)
Repurchase^2	-0.48						
	(0.306)						
Issuance^2	0.566***						
	(0.052)						
Size	-0.020**	-0.02**	-0.019**	-0.019**	-0.019**	-0.019**	-0.020**
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
BTM	0.046***	0.046***	0.045***	0.046***	0.046***	0.045***	0.046***
	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)	(0.017)
MissBTM	-0.062***	-0.062***	-0.071***	-0.071***	-0.069***	-0.067***	-0.064***
	(0.020)	(0.020)	(0.021)	(0.020)	(0.021)	(0.020)	(0.020)
Momentum	0.022	0.022	0.019	0.018	0.019	0.019	0.020
	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)	(0.025)
Constant	0.397***	0.396***	0.403***	0.396***	0.404***	0.397***	0.397***
	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)	(0.071)
R^2	0.0552	0.0543	0.0518	0.0517	0.0522	0.0533	0.0540
N	834828	834828	834828	834828	834828	834828	834828

Notes: This table displays the results of Fama-Macbeth cross-sectional regressions with the indicated predictor variables. The response variable is the 2-year cumulative stock return: the sum of the monthly holding period returns over the next 24 months. LargeRepurchase and SmallRepurchase are indicator variables that take on a value of 1 if the observation contained a repurchase larger or smaller than 9.3% of shares outstanding, respectively. LargeIssuance and SmallIssuance are indicator variables that take on a value of 1 if the observation contained an issuance larger or smaller than 1.4% of shares outstanding, respectively. RepurchIND and IssuanceIND are indicator variables that take on a value of 1 if the observation contained a repurchase or issuance, respectively. ChangeShares is the one-quarter percent change in shares outstanding. Repurchase is one-quarter percent decreases in shares outstanding. Issuance is one-quarter increases in shares outstanding. Size is the log of the market capitalization. BTM is the book-to-market ratio: the log of the book value of common equity divided by the market capitalization. MissBTM is the missing book-to-market indicator variable, which takes on a value of 1 if BTM is missing and is set to 0 otherwise. Momentum is the prior 6-month buy-and-hold return.

Column 2 shows the results of the Fama-Macbeth cross-sectional regressions using Equation 1.8. Using indicator variables for large and small share repurchases again confirms the previous findings. Firms making repurchases smaller than 9.3% of its shares outstanding and issuances smaller than 1.4% of its shares outstanding outperform, while firms that make large issuances underperform. As with the results shown in Column 1, the effect of large repurchases is insignificant. This is expected as only the largest repurchase bin had a negative coefficient in the binned regression, and the definition of large repurchases used in this regression groups observations in the two largest repurchase bins. Notably, the coefficient on small repurchases is significantly different the coefficient of large repurchases at the 5% significance level.[9]

The results in Column 3 and Column 4 highlight the central contributions of this paper. Column 3 shows a specification with just the change in shares outstanding variable can produce misleading results. Similar to the findings of Pontiff and Woodgate (2008), the coefficient is negative and significant. This result attaches the wrong sign to the effect of small issuances. The specification in Column 3 estimates a firm that issues 1% of its shares outstanding underperforms by 0.23% (conditional on the firm controls), while the more accurate specification in Column 1 predicts this firm would outperform by 1.7%. Further, the results in Column 3 severely underestimates the returns of firms who make small repurchases. The specification in Column 1 finds firms which make repurchases outperform by 4.3%. For a firm making a median-size repurchase of 1%, the linear specification predicts only an outperformance of 0.23%. The linear specification doesn't predict a firm would outperform by 4.3% until it repurchases 18.8% of its shares outstanding, which is larger than the 95th percentile of repurchases in the sample.

The results from a specification which only considers whether a repurchase or issuance was conducted and does not consider the magnitude of the repurchase or issuance is presented in Column 4. This model predicts firms which repurchase outperform by 3.6% and firms that issue shares have similar returns compared to a firm with no change in shares outstanding. Specifications which don't consider the size of issuances will miss the outperformance of firms making small

[9]The z-score of the two-sided test is 2.02, corresponding to a p-value of 0.022.

issuances and the underperformance of firms making large issuances.

Column 5 shows the results of splitting the change in shares outstanding variable into two separate slope variables for repurchases and issuances. As discussed in Section 1.2.2, the negative correlation between changes in shares outstanding and stock returns are driven almost entirely by the correlation between issuances and returns. These results are consistent with that finding. The coefficient on repurchases is insignificant, while the coefficient on issuances is significant and negative. The results in Columns 6-7 show the coefficient on the issuance indicator starts to become significantly negative once a slope coefficient is included, but separating the repurchase and issuance slope coefficients is needed to show larger repurchases don't predict higher returns.

1.5 Size and Book-to-Market Portfolios

Sections 1.3 and 1.4 find a non-linear relationship between changes in shares outstanding and returns when controlling linearly for size and book-to-market. However, firm size and book-to-market may have a non-linear effect on returns since firm characteristics may affect share repurchase and issuance behavior. For example, Covas and Den Haan (2011) documents that most firms tend to repurchase shares during recessions when their share prices are low, but the largest decile of firms by size tend to repurchase shares during economic expansions when their share prices are high. Failing to control for a possible non-linear relationship between the firm controls and returns may bias the estimates for repurchases and issuances.

To test whether the previously-found relationship between changes in shares outstanding and returns holds when controlling for firm size and book-to-market ratios non-linearly, I follow Ikenberry et al. (1995) and create size and book-to-market portfolios. Firm-quarter observations are sorted based on their size decile compared to other observations from their respective time periods. These firm-quarter observations are sorted into six portfolios: one portfolio for firms in each of the four smallest size quintiles and one portfolio for firms in each of the two largest size deciles. The largest quintile is split into two decile portfolios because firm size is right-skewed, so the largest firms can be very different from those in the 9th size decile.

To construct the book-to-market portfolios, the observations for each quarter and size decile are sorted into their book-to-market quintiles. Five book-to-market portfolios are formed, each holding the observations which fell into their respective book-to-market quintiles for their size decile and quarter. One additional book-to-market portfolio is formed for firm-quarter observations with a missing book-to-market ratio.

The results in Sections 1.3 and 1.4 are largely robust across the size and book-to-market portfolios. Small repurchases and issuances are correlated with higher returns and large issuances are correlated with lower returns across almost all portfolios. The main deviation from the previous results is small issuances have an insignificant effect on returns for the largest size portfolios and the smallest and largest book-to-market portfolios. I further find firms who make the largest repurchases tend to be small firms or those with missing or high book-to-market ratios.

1.5.1 Summary Statistics

Tables 1.8 and 1.9 compare the means of the regression variables in the full sample to their means in the size and book-to-market portfolios. Returns are negatively correlated with size and positively correlated with book-to-market (as discussed in Section 1.2.2), but this decomposition shows these relationships are non-linear. Firms in the smallest quintile have average 2-year returns 8.2% higher than firms in the next-highest size quintile, but the average 2-year returns only vary by less than 2% across the larger size quintiles. Similarly, firms with missing book-to-market ratios or in the lowest book-to-market quintile have much lower returns than those in higher book-to-market quintiles.

The distribution of repurchases and issuances also varies non-linearly across the size and book-to-market portfolios (see Tables 1.10 and 1.11), which suggests repurchase and issuance behavior may vary with these firm characteristics. For the median repurchases and issuances, the difference between firms in the 1st-2nd size deciles and firms in the 3rd-4th size deciles are as large as the difference between firms in the 3rd-4th size deciles and and firms in the 10th size decile. For the 99th percentile of repurchases, the difference between the 7th-8th and 10th size deciles are greater

Table 1.8: Means by size decile portfolios, 1975-2017

	ALL	1-2	3-4	5-6	7-8	9	10
Key Variables							
Return	0.279	0.353	0.271	0.254	0.258	0.262	0.253
ChangeShares	0.017	0.020	0.019	0.019	0.017	0.014	0.010
Repurchase	0.035	0.067	0.042	0.034	0.028	0.022	0.016
Issuance	0.050	0.091	0.060	0.048	0.040	0.034	0.028
Controls							
Size	5.07	2.45	3.94	4.96	6.06	7.17	8.68
BTM	-0.50	-0.08	-0.38	-0.52	-0.64	-0.76	-0.91
MissBTM	0.17	0.21	0.22	0.22	0.15	0.09	0.06
Momentum	0.07	-0.02	0.05	0.08	0.10	0.11	0.10

Notes: This table displays the summary statistics of the variables used in this analysis for the portfolios formed by size deciles. Return is the 2-year cumulative stock return: the sum of the monthly holding period returns over the next 24 months. ChangeShares is the one-quarter percent change in shares outstanding. Repurchase is one-quarter percent decreases in shares outstanding and only includes the sample which contains positive repurchases. Issuance is one-quarter increases in shares outstanding and only includes the sample which contains positive issuances. Size is the log of the market capitalization (in millions). BTM is the book-to-market ratio: the log of the book value of common equity divided by the market capitalization. The BTM statistics exclude observations with missing book-to-market values, for which the MissBTM dummy variable is set to 1. Momentum is the prior 6-month buy-and-hold return.

Table 1.9: Means by book-to-market decile portfolios, 1975-2017

	ALL	MISS	1-2	3-4	5-6	7-8	9-10
Key Variables							
Return	0.279	0.195	0.230	0.285	0.305	0.328	0.334
ChangeShares	0.017	0.031	0.024	0.015	0.012	0.011	0.011
Repurchase	0.035	0.096	0.021	0.019	0.019	0.021	0.038
Issuance	0.050	0.140	0.046	0.035	0.031	0.032	0.046
Controls							
Size	5.07	4.77	5.17	5.15	5.14	5.12	5.09
BTM	-0.50	N/A	-1.73	-0.84	-0.44	-0.11	0.58
MissBTM	0.17	1	0	0	0	0	0
Momentum	0.07	0.04	0.19	0.10	0.06	0.03	-0.02

Notes: This table displays the summary statistics of the variables used in this analysis for the portfolios formed by book-to-market deciles. Return is the 2-year cumulative stock return: the sum of the monthly holding period returns over the next 24 months. ChangeShares is the one-quarter percent change in shares outstanding. Repurchase is one-quarter percent decreases in shares outstanding and only includes the sample which contains positive repurchases. Issuance is one-quarter increases in shares outstanding and only includes the sample which contains positive issuances. Size is the log of the market capitalization (in millions). BTM is the book-to-market ratio: the log of the book value of common equity divided by the market capitalization. The BTM statistics exclude observations with missing book-to-market values, for which the MissBTM dummy variable is set to 1. Momentum is the prior 6-month buy-and-hold return.

than the difference between the 1st-2nd and 7th-8th size deciles.

Tables 1.12 and 1.13 compare the distributions of repurchases and issuances of the book-to-market portfolios to those of the full sample. Firms in the 3rd through 8th book-to-market deciles have similar distributions of repurchases and issuances. Firms in the 1st-2nd and 9th-10th book-to-market deciles make larger changes in shares outstanding, and firms with missing book-to-market ratios have the largest repurchases and issuances.

Table 1.10: Repurchase centiles (excl. zeroes) by size portfolios, 1975-2017

Deciles	25	50	75	90	95	99	% Rep
All	0.003	0.010	0.032	0.093	0.167	0.429	17%
1-2	0.003	0.017	0.078	0.218	0.333	0.441	14%
3-4	0.003	0.012	0.044	0.117	0.197	0.436	15%
5-6	0.002	0.010	0.035	0.093	0.153	0.355	14%
7-8	0.002	0.009	0.028	0.069	0.119	0.304	16%
9	0.003	0.009	0.023	0.054	0.088	0.212	20%
10	0.003	0.008	0.017	0.035	0.055	0.137	28%

Notes: This table displays the centiles of repurchases by size portfolios. Observations with zero or positive changes in shares outstanding are excluded when calculating repurchase centiles. Repurchase is one-quarter percent decreases in shares outstanding. % Rep is the fraction of firm-quarter observations with decreases in shares outstanding.

Table 1.11: Issuance centiles (excl. zeroes) by size portfolios, 1975-2017

Deciles	25	50	75	90	95	99	% Iss
All	0.001	0.005	0.022	0.130	0.262	1.000	47%
1-2	0.002	0.009	0.067	0.264	0.528	1.000	32%
3-4	0.001	0.005	0.029	0.162	0.329	1.000	43%
5-6	0.001	0.005	0.021	0.131	0.258	0.877	50%
7-8	0.001	0.004	0.017	0.107	0.206	0.660	55%
9	0.001	0.004	0.015	0.085	0.163	0.568	57%
10	0.001	0.003	0.011	0.060	0.121	0.538	52%

Notes: This table displays the centiles of issuances by size portfolios. Observations with zero or negative changes in shares outstanding are excluded when calculating issuance centiles. Issuance is one-quarter percent increases in shares outstanding. % Iss is the fraction of firm-quarter observations with increases in shares outstanding.

Overall, these statistics suggest the repurchase and issuance behavior of firms with different size and book-to-market ratios are qualitatively different in non-linear ways. Controlling for size

Table 1.12: Repurchase centiles (excl. zeroes) by BTM portfolios, 1975-2017

Deciles	25	50	75	90	95	99	% Rep
All	0.003	0.010	0.032	0.093	0.167	0.429	17%
Miss	0.015	0.054	0.133	0.257	0.373	0.441	15%
1-2	0.002	0.007	0.018	0.045	0.079	0.260	12%
3-4	0.002	0.007	0.018	0.043	0.073	0.200	16%
5-6	0.002	0.007	0.019	0.044	0.073	0.202	18%
7-8	0.002	0.008	0.022	0.048	0.081	0.204	19%
9-10	0.003	0.012	0.036	0.097	0.173	0.441	19%

Notes: This table displays the centiles of repurchases by book-to-market portfolios. Observations with zero or positive changes in shares outstanding are excluded when calculating repurchase centiles. Repurchase is one-quarter percent decreases in shares outstanding. % Rep is the fraction of firm-quarter observations with decreases in shares outstanding.

Table 1.13: Issuance centiles (excl. zeroes) by BTM portfolios, 1975-2017

Deciles	25	50	75	90	95	99	% Iss
All	0.001	0.005	0.022	0.130	0.262	1.000	47%
Miss	0.004	0.040	0.156	0.415	0.741	1.000	32%
1-2	0.002	0.006	0.025	0.120	0.216	0.843	59%
3-4	0.001	0.004	0.014	0.076	0.188	0.605	54%
5-6	0.001	0.003	0.011	0.060	0.164	0.574	50%
7-8	0.001	0.003	0.011	0.062	0.162	0.636	47%
9-10	0.001	0.004	0.017	0.106	0.234	0.994	40%

Notes: This table displays the centiles of issuances by book-to-market portfolios. Observations with zero or negative changes in shares outstanding are excluded when calculating issuance centiles. Issuance is one-quarter percent increases in shares outstanding. % Iss is the fraction of firm-quarter observations with increases in shares outstanding.

and book-to-market non-linearly may be important to ensure the results are robust across firms with different characteristics.

1.5.2 Results

For each of the size and book-to-market portfolios, I run Fama-Macbeth cross-sectional regressions using the polynomial specification (Equation 1.7). The estimates are compared to the results from the full-sample regressions. The largest firms and firms with the highest and lowest book-to-market ratios don't experience higher returns from small issuances, but the full-sample results are otherwise robust.

The results of the Fama-Macbeth regressions by size portfolio are similar to the full-sample results (see Table 1.14). Small repurchases predict significantly higher returns for all portfolios, and the coefficients on the slope and square repurchase terms are insignificant for all portfolios. Large issuances are associated with lower returns for all size portfolios, while small issuances are associated with higher returns for all but the 9th and 10th decile portfolios. These results show the key findings are largely robust to firm size.

The main findings are also largely robust to book-to-market ratios. Table 1.15 shows similar results for the polynomial Fama-Macbeth cross-sectional regressions. All book-to-market portfolios had a significant positive coefficient for small repurchases, and all portfolios except the missing book-to-market portfolio had a negative and significant slope coefficient for issuances. The main difference is the results for small issuances, where only the portfolios between the 3rd and 8th deciles had a positive and significant coefficient for the issuance indicator. The coefficient on the issuance indicator for the 9th-10th book-to-market decile portfolio has a similar magnitude, but its standard error is much larger.

Table 1.14: Fama-MacBeth regressions by size portfolios, 1975-2017

By Size	All	1-2	3-4	5-6	7-8	9	10
RepurchIND	**0.043*** **	**0.0349*** **	**0.0374*** **	**0.0483*** **	**0.0532*** **	**0.0415** **	**0.0388*** **
	(0.010)	(0.0117)	(0.0126)	(0.012)	(0.0106)	(0.0177)	(0.0134)
IssuanceIND	**0.023*** **	**0.0293*** **	**0.0348*** **	**0.0343*** **	**0.0379*** **	0.0127	0.0124
	(0.007)	(0.0076)	(0.0092)	(0.0109)	(0.008)	(0.012)	(0.0111)
Repurchase	0.021	-0.263	0.204	-0.297	-0.104	0.112	-3.922
	(0.160)	(0.224)	(0.355)	(0.969)	(0.268)	(3.743)	(4.137)
Issuance	**-0.635*** **	**-0.532** **	**-0.601*** **	**-0.552*** **	**-0.403* **	**-0.53*** **	**-0.596*** **
	(0.063)	(0.256)	(0.17)	(0.169)	(0.222)	(0.147)	(0.181)
Repurchase^2	-0.48	1.115	-1.258	23.91	9.061	-242.6	1242.7
	(0.306)	(1.316)	(1.533)	(28.59)	(8.161)	(592.1)	(1152.4)
Issuance^2	**0.566*** **	-1.562	-2.814	-0.155	-2.894	**1.544* **	0.7
	(0.052)	(1.614)	(3.302)	(0.688)	(3.242)	(0.93)	(0.613)
Size	-0.020**	-0.102***	-0.0091	-0.0033	-0.0123	0.0088	-0.0139
	(0.009)	(0.0186)	(0.0135)	(0.0142)	(0.0153)	(0.0109)	(0.0109)
BTM	0.046***	0.041**	0.0553***	0.0545***	0.0355**	0.0272	0.024
	(0.017)	(0.016)	(0.0187)	(0.0198)	(0.0176)	(0.0182)	(0.0152)
MissBTM	-0.062***	-0.0586***	-0.0507*	-0.0705***	-0.0454**	-0.0436*	-0.0102
	(0.020)	(0.0221)	(0.0265)	(0.0205)	(0.0204)	(0.023)	(0.0159)
Momentum	0.022	-0.0155	0.0394	0.055*	0.0521	0.0378	0.0337
	(0.025)	(0.0308)	(0.0291)	(0.0294)	(0.0318)	(0.0284)	(0.0278)
Constant	0.397***	0.588***	0.326***	0.294***	0.34***	0.203***	0.366***
	(0.071)	(0.0811)	(0.0816)	(0.0867)	(0.093)	(0.078)	(0.0908)
R^2	0.0552	0.0435	0.0476	0.0530	0.0547	0.0745	0.0889
N	834828	166856	166982	166972	166970	83473	83575

Notes: This table displays the results of Fama-Macbeth cross-sectional regressions by size portfolio with the indicated predictor variables. The columns indicate which size deciles are used in the regression. The response variable is the 2-year cumulative stock return: the sum of the monthly holding period returns over the next 24 months. RepurchIND and IssuanceIND are indicator variables that take on a value of 1 if the observation contained a repurchase or issuance, respectively. Repurchase is one-quarter percent decreases in shares outstanding. Issuance is one-quarter increases in shares outstanding. Size is the log of the market capitalization. BTM is the book-to-market ratio: the log of the book value of common equity divided by the market capitalization. MissBTM is the missing book-to-market indicator variable, which takes on a value of 1 if BTM is missing and is set to 0 otherwise. Momentum is the prior 6-month buy-and-hold return.

Table 1.15: Fama-MacBeth regressions by book-to-market portfolios, 1975-2017

By BM	All	Missing	1-2	3-4	5-6	7-8	9-10
RepurchIND	**0.043*****	**0.109*****	**0.0348****	**0.0308****	**0.0361*****	**0.0457****	**0.0427*****
	(0.010)	(0.0373)	(0.0146)	(0.0124)	(0.009)	(0.0224)	(0.0145)
IssuanceIND	**0.023*****	-0.0113	0.0141	**0.0243*****	**0.0248*****	**0.0258*****	0.0235
	(0.007)	(0.0152)	(0.0141)	(0.007)	(0.0059)	(0.0094)	(0.0143)
Repurchase	0.021	-60.62	-2.117	1.287	0.126	-6.261	0.443
	(0.160)	(49.42)	(2.071)	(0.925)	(0.459)	(6.721)	(0.309)
Issuance	**-0.635*****	21.27	**-0.772*****	**-0.616*****	**-0.826*****	**-0.679*****	**-0.409*****
	(0.063)	(19.94)	(0.119)	(0.128)	(0.185)	(0.122)	(0.118)
$Repurchase^2$	-0.48	530.3	79.3	-32.68	21.33	609.6	-4.218*
	(0.306)	(422.8)	(79.12)	(24.97)	(16.47)	(598.5)	(2.179)
$Issuance^2$	**0.566*****	-15715.9	**0.713*****	-0.716	7.812	6.068	0.416
	(0.052)	(15445.5)	(0.126)	(1.113)	(7.322)	(4.803)	(0.976)
Size	-0.020**	-0.0243**	-0.0092	-0.0142	-0.0102	-0.0163**	-0.032***
	(0.009)	(0.0093)	(0.013)	(0.0095)	(0.0072)	(0.007)	(0.0079)
BTM	0.046***		0.0666***	0.107**	0.134***	0.123***	0.0017
	(0.017)		(0.0198)	(0.0429)	(0.0282)	(0.0342)	(0.0167)
MissBTM	-0.062***						
	(0.020)						
Momentum	0.022	0.034	0.001	0.0251	0.0404	0.0198	0.058
	(0.025)	(0.0344)	(0.0177)	(0.0276)	(0.03)	(0.0375)	(0.0388)
Constant	0.397***	0.35***	0.392***	0.437***	0.383***	0.394***	0.477***
	(0.071)	(0.0745)	(0.0873)	(0.0699)	(0.0631)	(0.0594)	(0.0721)
R^2	0.0552	0.0777	0.0556	0.0552	0.0538	0.0610	0.0530
N	834828	145992	137082	137772	137806	137765	138411

Notes: This table displays the results of Fama-Macbeth regressions by size portfolio with the indicated predictor variables. The columns indicate which size deciles are used in the regression. The response variable is the 2-year cumulative stock return: the sum of the monthly holding period returns over the next 24 months. RepurchIND and IssuanceIND are indicator variables that take on a value of 1 if the observation contained a repurchase or issuance, respectively. Repurchase is one-quarter percent decreases in shares outstanding. Issuance is one-quarter increases in shares outstanding. Size is the log of the market capitalization. BTM is the book-to-market ratio: the log of the book value of common equity divided by the market capitalization. MissBTM is the missing book-to-market indicator variable, which takes on a value of 1 if BTM is missing and is set to 0 otherwise. Momentum is the prior 6-month buy-and-hold return.

1.6 2003-2017 Subsample

Fu and Huang (2016) find the relationship between net issuances and returns ”weakens substantially” after 2003. They argue these findings suggest firms make share repurchases and issuances less frequently to take advantage of mispricing and more frequently for cash flow needs in this recent period. The increased prevalence of institutional investors and more stringent accounting standards also reduced the amount of stock mispricings that managers could take advantage of with share repurchases and issuances.

Unlike Fu and Huang (2016), I find no conclusive evidence that the effects of share repurchases and issuances have changed after 2003. The effect of large issuances remains significantly negative. The effect of small repurchases and issuances become insignificant, but this is driven by larger standard errors. These results suggest changes in shares outstanding may still provide information on future stock returns after 2003. The use of one-quarter as opposed to one-year changes in shares outstanding is responsible for much of this difference in results. As I discuss in Section 1.7.2, using the higher-frequency measure of changes in shares outstanding mitigates the decrease in the coefficients from the full sample to the post-2003 subsample.

1.6.1 Summary Statistics

Table 1.16 shows the summary statistics of the variables for the 2003-2017 subsample. Overall, the summary statistics are similar to those of the full sample. The average log size of firms in the subsample is 0.86 larger, which corresponds to the average size of firms being roughly 2.4 times larger. Returns are roughly 7% smaller than in the full sample. The means and standard deviations for the change in shares outstanding, book-to-market, and momentum variables of the 2003-2017 subsample are similar to those of the full sample. As Table 1.17 indicates, the distributions of repurchases and issuances in the 2003-2017 subsample are also similar to those of the full sample.

Tables 1.18 and 1.19 shows the contemporaneous correlations between the variables in the 2003-2017 subsample. The correlation between returns and the change in shares outstanding

Table 1.16: Summary statistics, 2003-2017

	Mean	SD	1%	25%	50%	75%	99%	N
Key Variables								
Return	0.21	0.62	-1.84	-0.04	0.20	0.48	2.12	339444
ChangeShares	0.02	0.11	-0.20	0.00	0.00	0.01	0.68	339444
Repurchases	0.04	0.08	0.00	0.00	0.01	0.04	0.44	70886
Issuances	0.06	0.15	0.00	0.00	0.00	0.02	1.00	184967
Controls								
Size	5.93	2.02	1.37	4.52	5.87	7.30	10.45	339444
BTM	-0.58	1.01	-3.25	-1.14	-0.58	-0.07	2.74	252000
Momentum	0.06	0.32	-0.66	-0.10	0.04	0.18	1.43	339444

Notes: This table compares the summary statistics of the variables for the full sample and the 2003-2017 subsample. Return is the 2-year cumulative stock return: the sum of the monthly holding period returns over the next 24 months. ChangeShares is the one-quarter percent change in shares outstanding. Repurchase is one-quarter percent decreases in shares outstanding, and excludes observations with no repurchases. Issuance is one-quarter increases in shares outstanding, and excludes observations with no issuances. Size is the log of the market capitalization (in millions). BTM is the book-to-market ratio: the log of the book value of common equity divided by the market capitalization. The BTM statistics exclude observations with missing book-to-market values which comprise 16.4% of the sample. Momentum is the prior 6-month buy-and-hold return.

Table 1.17: Repurchase and issuance centiles (excl. zeroes)

This table compares the repurchase and issuance centiles for the full sample and the 2003-2017 subsample. Observations with zero repurchases are excluded when calculating repurchase centiles, and observations with zero issuances are excluded when calculating issuance centiles. Repurchase is one-quarter percent decreases in shares outstanding. Issuance is one-quarter increases in shares outstanding.

Centile	25	50	75	90	95	99	Mean	SD
1975-2017								
Repurchase	0.003	0.010	0.032	0.093	0.167	0.429	0.035	0.070
Issuance	0.001	0.005	0.022	0.130	0.262	1.000	0.050	0.142
2003-2017								
Repurchase	0.003	0.011	0.037	0.111	0.200	0.441	0.040	0.076
Issuance	0.001	0.005	0.024	0.152	0.297	1.000	0.056	0.151

Table 1.18: Contemporaneous correlations, 2003-2017

	Return	ChangeShares	Size	BTM	MissBTM
ChangeShares	-0.046				
Size	-0.020	-0.061			
BTM	0.084	-0.006	-0.309		
MissBTM	-0.061	-0.109	0.224	N/A	
Momentum	-0.040	0.027	0.109	-0.195	-0.045

Notes: This table displays the contemporaneous correlations between the main variables. Correlations are calculated including observations with zero change in shares outstanding. Return is the 2-year cumulative stock return: the sum of the monthly holding period returns over the next 24 months. ChangeShares is the one-quarter percent change in shares outstanding. Size is the log of the market capitalization. BTM is the book-to-market ratio: the log of the book value of common equity divided by the market capitalization. The correlations for BTM are calculated excluding observations with missing BTM values. MissBTM is the missing book-to-market indicator variable, which takes on a value of 1 if BTM is missing and is set to 0 otherwise. Momentum is the prior 6-month buy-and-hold return.

Table 1.19: Contemporaneous correlations, 2003-2017

	ChangeShares	RepurchIND	IssuanceIND	Repurchase	Issuance
Return	-0.046	0.017	-0.010	-0.054	-0.062
Size	-0.061	0.155	0.132	-0.340	-0.176
BTM	-0.006	0.002	-0.173	0.256	0.073
MissBTM	-0.109	-0.032	-0.210	0.506	0.345
Momentum	0.027	-0.057	0.085	-0.013	-0.006

Notes: This table displays the contemporaneous correlations between changes in shares outstanding, repurchase, and issuance variables and the other main variables. Correlations displayed for the Repurchase and Issuance variables are calculated excluding observations with zero repurchases and issuances, respectively. Return is the 2-year cumulative stock return: the sum of the monthly holding period returns over the next 24 months. ChangeShares is the one-quarter percent change in shares outstanding. RepurchIND and IssuanceIND are indicator variables that take on a value of 1 if the observation contained a repurchase or issuance, respectively. Repurchase is one-quarter percent decreases in shares outstanding. Issuance is one-quarter increases in shares outstanding. Size is the log of the market capitalization. BTM is the book-to-market ratio: the log of the book value of common equity divided by the market capitalization. The correlations for BTM are calculated excluding observations with missing BTM values. MissBTM is the missing book-to-market indicator variable, which takes on a value of 1 if BTM is missing and is set to 0 otherwise. Momentum is the prior 6-month buy-and-hold return.

variables in the recent subsample are similar to those of the full sample. Like in the full sample, large firms are more likely to make repurchases and issuances. These repurchases and issuances tend to be smaller in the full sample and are much smaller in the 2003-2017 subsample.

There are many differences between the full sample and the 2003-2017 subsample in the correlations between book-to-market and the repurchase and issuance variables. The correlation between the book-to-market ratio and changes in shares outstanding switches from negative in the full sample to positive in the recent subsample. High book-to-market firms are less likely to make repurchases and make much larger repurchases and issuances in the recent subsample as compared to the full sample. Repurchases made by high book-to-market firms have been used as examples of repurchases which take advantage of mispricing (e.g. Pontiff and Woodgate (2008)). Fu and Huang (2016) cite this change in correlations as evidence that mispricing is less likely to be the motivation for repurchases and issuances in the 2003-2017 period.

1.6.2 Fama-MacBeth Regressions

Table 1.20 compares the Fama-MacBeth cross-sectional regression results for the 2003-2017 subsample with the full sample results. The effects of small and large issuances remain significant in the 2003-2017 subsample, although the outperformance of firms who make small issuances is now only significant at the 10% level.

Column 1 shows the coefficients on the issuance variables in the polynomial specification are all significant in the 2003-2017 subsample, and these coefficients have the same sign and have similar values compared to the coefficients in the full sample. Unlike the full sample, the coefficient on small repurchases becomes insignificant in the subsample primarily due to the increase in the standard error. Similarly, the coefficients of the indicator specification shown in Column 2 show the same results, with the issuance coefficients remaining significant and having the same sign, while the coefficient on small repurchases becomes insignificant.

Unlike Fu and Huang (2016), I find no conclusive evidence that these coefficients have changed.[10]

[10] This finding is not driven by the additional years contained in this subsample. With 2003-2013 subsample,

Table 1.20: Fama-MacBeth regressions, 2003-2017

	(1)		(2)		(3)	
	Full	03-17	Full	03-17	Full	03-17
LargeRepurchase			0.006	-0.0085		
			(0.016)	(0.011)		
SmallRepurchase			0.043***	0.0277		
			(0.009)	(0.0202)		
SmallIssuance			0.027***	0.0312*		
			(0.007)	(0.0159)		
LargeIssuance			-0.049***	-0.0457***		
			(0.010)	(0.0074)		
RepurchIND	0.043***	0.0327				
	(0.010)	(0.0247)				
IssuanceIND	0.023***	0.0276*				
	(0.007)	(0.0163)				
ChangeShares					-0.229***	-0.183***
					(0.03)	(0.02)
Repurchase	0.021	-0.189				
	(0.160)	(0.26)				
Issuance	-0.635***	-0.529***				
	(0.063)	(0.07)				
$Repurchase^2$	-0.48	-0.0657				
	(0.306)	(0.486)				
$Issuance^2$	0.566***	0.415***				
	(0.052)	(0.0502)				
Size	-0.020**	0.0015	-0.02**	0.0021	-0.019**	0.0034
	(0.009)	(0.0053)	(0.009)	(0.0052)	(0.009)	(0.0047)
BTM	0.046***	0.0182*	0.046***	0.0181*	0.045***	0.0151
	(0.017)	(0.0099)	(0.017)	(0.0098)	(0.017)	(0.0105)
MissBTM	-0.062***	-0.0606***	-0.062***	-0.0625***	-0.071***	-0.0745***
	(0.020)	(0.0225)	(0.020)	(0.0228)	(0.021)	(0.0262)
Momentum	0.022	-0.0019	0.022	-0.0004	0.019	-0.0064
	(0.025)	(0.051)	(0.025)	(0.0512)	(0.025)	(0.0514)
Constant	0.397***	0.185**	0.396***	0.182**	0.403***	0.19**
	(0.071)	(0.0803)	(0.071)	(0.0803)	(0.071)	(0.0837)
R^2	0.0552	0.0358	0.0543	0.0347	0.0518	0.0320
N	834828	339444	834828	339444	834828	339444

Notes: This table compares the results of Fama-Macbeth cross-sectional regressions with the indicated predictor variables of the full sample with the 2003-2017 subsample. The response variable is the 2-year cumulative stock return: the sum of the monthly holding period returns over the next 24 months. LargeRepurchase and SmallRepurchase are indicator variables that take on a value of 1 if the observation contained a repurchase larger or smaller than 9.3% of shares outstanding, respectively. LargeIssuance and SmallIssuance are indicator variables that take on a value of 1 if the observation contained an issuance larger or smaller than 1.4% of shares outstanding, respectively. RepurchIND and IssuanceIND are indicator variables that take on a value of 1 if the observation contained a repurchase or issuance, respectively. ChangeShares is the one-quarter percent change in shares outstanding. Repurchase is one-quarter percent decreases in shares outstanding. Issuance is one-quarter increases in shares outstanding. Size is the log of the market capitalization. BTM is the book-to-market ratio: the log of the book value of common equity divided by the market capitalization. MissBTM is the missing book-to-market indicator variable, which takes on a value of 1 if BTM is missing and is set to 0 otherwise. Momentum is the prior 6-month buy-and-hold return.

Fu and Huang (2016) finds the magnitude of the one-year change in shares outstanding coefficient decreases significantly by 66%. Column 3 shows the coefficient on one-quarter changes in shares outstanding only decreased by 20% from the full sample to the 2003-2017 subsample, and the difference is not statistically significant (z-score of 1.28). The coefficients on the repurchase indicator in Column 1 and the small repurchase indicator in Column 2 shrink, but again these differences are not significant (z-score of 0.69). The coefficients on the issuance indicator in Column 1 and small issuance indicator in Column 2 are larger in magnitude for the subsample than in the full sample. For these variables, any loss of significance is driven by the larger standard errors.

One major difference between this study and Fu and Huang (2016) is the use of one-quarter versus one-year changes in shares outstanding. As shown in Section 1.7.2, using one-year changes in shares outstanding produces a much larger decline in coefficient values for the post-2003 subsample compared to the full sample. This suggests using higher-frequency data is needed to capture the effects of repurchases and issuances, possibly due to the increased frequency of repurchases and issuances in the recent data.

1.7 Robustness

Compared to the methodology of Pontiff and Woodgate (2008), this study differs in three major ways. This study uses cumulative returns instead of buy-and-hold returns, one-quarter changes in shares outstanding instead of one-year changes, and contemporaneous predictor variables instead of 6-months lagged predictor variables. In this section, I test whether the results of the Fama-MacBeth cross-sectional regressions in Section 1.4 are sensitive to these differences. Overall, the earlier results are robust to these different specifications.

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the coefficient on small issuances becomes insignificant but there are still no significant differences between the coefficients in the subsample compared to those of the full sample.

1.7.1 Buy-And-Hold Returns

In this section, I examine whether the main findings presented in Sections 1.3 and 1.4 are robust to using buy-and-hold returns. As discussed in Section 1.2, the analyses in the previous sections use cumulative returns instead of buy-and-hold returns. These two measures have almost identical means, but buy-and-hold returns exhibit a strong right skew while cumulative returns are nearly symmetric. The main concern with using cumulative returns is it overestimates the returns of volatile assets for buy-and-hold investors.

To test whether the main findings are robust to using buy-and-hold returns, I rerun Equations 1.7 and 1.8 replacing cumulative returns with buy-and-hold returns:

$$BHReturn_{i,t+1,t+24} = \left[\prod_{\tau=t+1}^{t+24}(1 + MonthlyReturn_{i,\tau})\right] - 1$$

Table 1.21 compares the results of using cumulative returns with the results using buy-and-hold returns. These results show the main findings of the previous sections are robust to using buy-and-hold returns. Using buy-and-hold returns tends to produce larger coefficient estimates than those produced by cumulative returns due to its greater skewness. Overall, the results are qualitatively identical and the coefficients are similar in magnitude.

1.7.2 One-Year Changes in Shares Outstanding

In this section, I examine whether the main findings of my analysis are robust to using one-year windows to calculate repurchases and issuances. Pontiff and Woodgate (2008) use one-year changes in shares outstanding in their analysis. Exchange-traded funds that track the performance of repurchasing firms also use one-year changes in shares outstanding to select firms for inclusion in their portfolios.

To ensure I use the same repurchase and issuance data as in the main analysis, I exclude the first six quarters of each firm's observations. Table 1.22 compares the distributions of one-quarter and one-year repurchases and issuances. Excluding the first six quarters slightly decreases

Table 1.21: Fama-MacBeth regressions with buy-and-hold returns, 1975-2017

	(1)		(2)		(3)	
	CR	BHR	CR	BHR	CR	BHR
LargeRepurchase			0.006	0.0312		
			(0.016)	(0.0246)		
SmallRepurchase			0.043***	0.061***		
			(0.009)	(0.0102)		
SmallIssuance			0.027***	0.0291***		
			(0.007)	(0.0095)		
LargeIssuance			-0.049***	-0.0593***		
			(0.010)	(0.0145)		
RepurchIND	0.043***	0.0569***				
	(0.010)	(0.0107)				
IssuanceIND	0.023***	0.0235**				
	(0.007)	(0.0094)				
ChangeShares					-0.229***	-0.285***
					(0.03)	(0.0347)
Repurchase	0.021	0.258				
	(0.160)	(0.213)				
Issuance	-0.635***	-0.707***				
	(0.063)	(0.0828)				
Repurchase^2	-0.48	-0.824				
	(0.306)	(0.658)				
Issuance^2	0.566***	0.604***				
	(0.052)	(0.0758)				
Size	-0.020**	-0.0089	-0.02**	-0.0088	-0.019**	-0.0072
	(0.009)	(0.0105)	(0.009)	(0.0105)	(0.009)	(0.0105)
BTM	0.046***	0.072***	0.046***	0.0715***	0.045***	0.0714***
	(0.017)	(0.0213)	(0.017)	(0.0212)	(0.017)	(0.0218)
MissBTM	-0.062***	-0.0558**	-0.062***	-0.0558**	-0.071***	-0.0652***
	(0.020)	(0.0243)	(0.020)	(0.0243)	(0.021)	(0.0248)
Momentum	0.022	0.0736**	0.022	0.0743**	0.019	0.0705**
	(0.025)	(0.0328)	(0.025)	(0.0327)	(0.025)	(0.0332)
Constant	0.397***	0.358***	0.396***	0.357***	0.403***	0.364***
	(0.071)	(0.0836)	(0.071)	(0.0837)	(0.071)	(0.0841)
R^2	0.0552	0.0488	0.0543	0.0483	0.0518	0.0453
N	834828	834828	834828	834828	834828	834828

Notes: This table compares the results of Fama-Macbeth cross-sectional regressions with cumulative returns (CR) against the results with buy-and-hold returns (BHR). The response variable is the 2-year cumulative stock return: the sum of the monthly holding period returns over the next 24 months. LargeRepurchase and SmallRepurchase are indicator variables that take on a value of 1 if the observation contained a repurchase larger or smaller than 8.5% of shares outstanding, respectively. LargeIssuance and SmallIssuance are indicator variables that take on a value of 1 if the observation contained an issuance larger or smaller than 1.36% of shares outstanding, respectively. RepurchIND and IssuanceIND are indicator variables that take on a value of 1 if the observation contained a repurchase or issuance, respectively. ChangeShares is the change in shares outstanding: the percent change in shares outstanding over the three months. Repurchase is one-quarter percent decreases in shares outstanding. Issuance is one-quarter increases in shares outstanding. Size is the log of the market capitalization. BTM is the book-to-market ratio: the log of the book value of common equity divided by the market capitalization. MissBTM is the missing book-to-market indicator variable, which takes on a value of 1 if BTM is missing and is set to 0 otherwise. Momentum is the prior 6-month buy-and-hold return.

the magnitude of the largest 1-quarter repurchases and issuances in the sample. The mean one-year issuance is 3.5 times larger than the mean one-quarter issuance, while the mean one-year repurchase is 1.9 times larger than the one-quarter repurchase. The smaller difference for repurchases is expected since repurchases must be less than 1.

Table 1.22: One-year vs. one-quarter repurchase and issuance centiles, 1975-2017

Centile	25	50	75	90	95	99	Mean	SD
1 Quarter								
Repurchase	0.003	0.010	0.031	0.089	0.160	0.398	0.034	0.067
Issuance	0.001	0.004	0.020	0.117	0.236	0.872	0.046	0.133
1 Year								
Repurchase	0.008	0.027	0.070	0.170	0.286	0.594	0.065	0.105
Issuance	0.006	0.022	0.119	0.378	0.724	2.727	0.161	0.438

Notes: This table compares the centiles of one-quarter repurchases and issuances with the centiles of one-year repurchases and issuances. The first six quarters of observations are excluded for each firm. Observations with zero repurchase are excluded when calculating repurchase centiles, and observations with zero issuance are excluded when calculating issuance centiles. Repurchase is one-quarter or one-year percent decreases in shares outstanding. Issuance is one-quarter or one-year increases in shares outstanding.

I run Fama-MacBeth cross-sectional regressions using the specification in Equation 1.7 with one-year changes in shares outstanding. These results are compared it to the results using one-quarter changes in shares outstanding. As shown in Table 1.24, the main findings are robust to using one-year changes in shares outstanding. The predicted effect of one-year issuances turns negative at 9.8% of shares outstanding. This value is around the 70th percentile of one-year issuances. For comparison, the estimated effect of one-quarter issuances turns negative around the 80th percentile in the polynomial specification.

Using one-year changes in shares outstanding for the 2003-2017 subsample produces results which more closely match those of Fu and Huang (2016). The magnitude of the slope coefficient for change in shares outstanding shrinks by 41%. While this decline is still smaller than the two-thirds decline in Fu and Huang (2016), it is twice the size of the decline of the coefficient for the 1-quarter change in shares outstanding. The magnitude of the coefficient on the 1-year issuance indicator also falls by roughly one-third, compared to slightly increasing for the 1-quarter issuance

Table 1.23: Fama-MacBeth regressions with 1-year repurchases/issuances, 1975-2017

	(1)			(2)		
	1Q Full	1YR Full	1YR 03-17	1Q Full	1YR Full	1YR 03-17
RepurchInd	0.039***	0.042***	0.02			
	(0.011)	(0.014)	(0.036)			
IssuanceIND	0.02**	0.024**	0.016			
	(0.008)	(0.009)	(0.022)			
ChangeShares				-0.23***	-0.121***	-0.071***
				(0.03)	(0.016)	(0.011)
Repurchase	0.082	0.147	-0.081			
	(0.158)	(0.118)	(0.167)			
Issuance	-0.628***	-0.268***	-0.202***			
	(0.058)	(0.027)	(0.016)			
Repurchase^2	-0.534	-0.58**	-0.105			
	(0.38)	(0.237)	(0.268)			
Issuance^2	0.591***	0.079***	0.054***			
	(0.052)	(0.01)	(0.005)			
Size	-0.022**	-0.022**	-0.000	-0.02**	-0.021**	0.001
	(0.009)	(0.009)	(0.006)	(0.009)	(0.009)	(0.005)
BTM	0.046***	0.044***	0.022*	0.045***	0.043**	0.02*
	(0.017)	(0.016)	(0.011)	(0.017)	(0.017)	(0.012)
MissBTM	-0.064***	-0.062***	-0.065**	-0.072***	-0.069***	-0.071**
	(0.02)	(0.02)	(0.026)	(0.021)	(0.021)	(0.03)
Momentum	0.018	0.012	-0.015	0.015	0.011	-0.018
	(0.027)	(0.027)	(0.059)	(0.027)	(0.027)	(0.059)
Constant	0.417***	0.415***	0.214**	0.422***	0.427***	0.214**
	(0.071)	(0.069)	(0.085)	(0.072)	(0.072)	(0.096)
R^2	0.0565	0.0595	0.0372	0.0530	0.0548	0.0328
N	734288	734288	276120	734288	734288	276120

Notes: This table compares the results of Fama-Macbeth cross-sectional regressions with one-quarter (1QT Full) and one-year (1YR Full) changes in shares outstanding in the full sample, as well as the one-year changes in the 2003-2017 subsample (1YR 03-17). The response variable is the 2-year cumulative stock return: the sum of the monthly holding period returns over the next 24 months. RepurchIND and IssuanceIND are indicator variables that take on a value of 1 if the observation contained a repurchase or issuance, respectively. ChangeShares is the one-quarter or one-year percent change in shares outstanding. Repurchase is one-quarter or one-year percent decreases in shares outstanding. Issuance is one-quarter or one-year increases in shares outstanding. Size is the log of the market capitalization. BTM is the book-to-market ratio: the log of the book value of common equity divided by the market capitalization. MissBTM is the missing book-to-market indicator variable, which takes on a value of 1 if BTM is missing and is set to 0 otherwise. Momentum is the prior 6-month buy-and-hold return.

indicator. This finding suggests the use of a shorter window for repurchases and issuances may be more informative for predicting future returns in the recent period.

1.7.3 Lagged Predictor Variables

Finally, I test whether the main findings can be explained by a mismatch between the recorded dates of observations in Computstat and the date this information was released. Observations in Compustat are recorded by the final month of the reporting period, but financial reports containing that information only become available weeks after the end of the reporting period at the earliest. As such, traders cannot legally use contemporaneous data to form their trading strategies.

Pontiff and Woodgate (2008) address this concern by lagging the predictor variables by 6 months to allow the information to be fully reported to the market. I rerun Equations 1.7 and 1.8 while lagging all predictor variables by six months and confirm the main findings are robust. Table 1.23 shows the results of these regressions. The results with the lagged predictor variables are qualitatively identical to those of the base regression, and the coefficients are similar in magnitude. While the coefficient on squared repurchases becomes significant and negative with the lagged predictor variables, the magnitude of the repurchase where the effect is predicted to become negative has actually increased compared to the baseline results. These results show the findings are not caused by the timing of information used in this analysis. Instead, they show most of the stock price adjustment in response to the information in share repurchases and issuances occurs 6 months after those events.

1.8 Conclusion

The existing literature on the effects of share repurchases and issuances on long-run returns ignores the size of repurchases or issuances, or only considers a linear specification of changes in shares outstanding. However, there are large differences in magnitude between the median repurchases and issuances and the largest repurchases and issuances. This difference raises concerns that small

Table 1.24: Fama-MacBeth regressions with lagged predictor variables, 1975-2017

	(1)		(2)		(3)	
	Base	Lagged	Base	Lagged	Base	Lagged
LargeRepurchase			0.006	-0.0018		
			(0.016)	(0.0147)		
SmallRepurchase			0.043***	0.0362***		
			(0.009)	(0.009)		
SmallIssuance			0.027***	0.0262***		
			(0.007)	(0.0086)		
LargeIssuance			-0.049***	-0.0478***		
			(0.010)	(0.0097)		
RepurchIND	0.043***	0.0348***				
	(0.010)	(0.01)				
IssuanceIND	0.023***	0.024***				
	(0.007)	(0.0085)				
ChangeShares					-0.229***	-0.241***
					(0.03)	(0.0321)
Repurchase	0.021	0.149				
	(0.160)	(0.186)				
Issuance	-0.635***	-0.673***				
	(0.063)	(0.0746)				
$Repurchase^2$	-0.48	-1.257**				
	(0.306)	(0.532)				
$Issuance^2$	0.566***	0.605***				
	(0.052)	(0.0756)				
Size	-0.020**	-0.0211**	-0.02**	-0.0209**	-0.019**	-0.0199**
	(0.009)	(0.0091)	(0.009)	(0.0091)	(0.009)	(0.009)
BTM	0.046***	0.0302*	0.046***	0.0298*	0.045***	0.0286
	(0.017)	(0.0171)	(0.017)	(0.0171)	(0.017)	(0.0175)
MissBTM	-0.062***	-0.0507**	-0.062***	-0.0517**	-0.071***	-0.0595***
	(0.020)	(0.0199)	(0.020)	(0.02)	(0.021)	(0.0211)
Momentum	0.022	-0.0253	0.022	-0.0253	0.019	-0.0286
	(0.025)	(0.0285)	(0.025)	(0.0284)	(0.025)	(0.0286)
Constant	0.397***	0.405***	0.396***	0.404***	0.403***	0.41***
	(0.071)	(0.0712)	(0.071)	(0.0713)	(0.071)	(0.0718)
R^2	0.0552	0.0481	0.0543	0.0467	0.0518	0.0446
N	834828	797759	834828	797759	834828	797759

Notes: This table compares the results of Fama-Macbeth cross-sectional regressions with contemporaneous returns (Base) against the results with predictor variables lagged by 6 months (Lagged). The response variable is the 2-year cumulative stock return: the sum of the monthly holding period returns over the next 24 months. LargeRepurchase and SmallRepurchase are indicator variables that take on a value of 1 if the observation contained a repurchase larger or smaller than 8.5% of shares outstanding, respectively. LargeIssuance and SmallIssuance are indicator variables that take on a value of 1 if the observation contained an issuance larger or smaller than 1.36% of shares outstanding, respectively. RepurchIND and IssuanceIND are indicator variables that take on a value of 1 if the observation contained a repurchase or issuance, respectively. ChangeShares is the one-quarter percent change in shares outstanding. Repurchase is one-quarter percent decreases in shares outstanding. Issuance is one-quarter increases in shares outstanding. Size is the log of the market capitalization. BTM is the book-to-market ratio: the log of the book value of common equity divided by the market capitalization. MissBTM is the missing book-to-market indicator variable, which takes on a value of 1 if BTM is missing and is set to 0 otherwise. Momentum is the prior 6-month buy-and-hold return.

and large repurchases and issuances may contain different information on future stock returns.

I find the relationship between changes in shares outstanding and returns is non-linear. Firms making repurchases and issuances smaller than 9.3% and 1.4% of shares outstanding, respectively, have higher 2-year returns compared to firms with no changes in shares outstanding. Firms making larger repurchases and issuances have lower returns. While some of these predictive effects become less significant in the 2003-2017 subsample, I find no evidence that the predicted effect changes between the full sample and the subsample. Specifications which don't allow for this non-linearity produce misleading results which may lead investors to incorrectly overweight firms with large repurchases and underweight firms with small repurchases and issuances.

Chapter 2

Performance of repurchase and issuance portfolios from 2003-2019

2.1 Introduction

Can investors use share repurchase and issuance information to outperform the market? Previous studies have found that firms which repurchase shares have higher future stock returns than non-repurchasing firms (e.g., Ikenberry et al. (1995), Peyer and Vermaelen (2009), Pontiff and Woodgate (2008)). These studies encouraged the creation of mutual funds which invest in repurchasing firms. The largest exchange-traded fund (ETF) that invests in repurchasing firms, the Invesco Powershares Buyback Achievers Fund, had $1.5 billion in assets under management in November 2018 (Invesco Distributors, Inc., 2018).

However, there are several reasons why these previous studies may not reflect options available to investors and fund managers. First, the previously-found relationship between share repurchases and stock returns may no longer hold after 2003. Fu and Huang (2016) find the effect of repurchases and issuances on stock returns shrinks dramatically and is often insignificant for the more recent 2003-2015 period. Second, the studies examining the effect of repurchases and issuances (e.g., Pontiff and Woodgate (2008), Fu and Huang (2016)) include all stocks traded on U.S. stock exchanges. These samples include American depository receipts, real estate investment trusts, and exchange-traded funds. Many fund managers may be restricted from investing in foreign companies or other funds, and these entities may have different share repurchase and issuance behaviors than those of U.S. firms. Finally, these studies do not consider the effect of transaction costs on portfolio returns.

In this paper, I examine whether share repurchase and issuance information can be used to construct portfolios which outperform the market using data from 2003 to 2019. I first evaluate the performance of the Invesco Buyback Achievers Fund and the SPDR Buyback ETF. These are the ETFs which exlusively invest in US companies that have repurchased shares in the past year, and both were founded after 2003. For each of these portfolios, I calculate the Sharpe (1994) Ratio and the excess return over the risk-free rate using the calendar-time approach of Mitchell and Stafford (2000). I find no evidence these ETFs outperformed the market portfolios, which supports the findings of Fu and Huang (2016).

While the repurchase ETFs don't consistently outperform the market, there may be other methods to construct portfolios using repurchase and issuance information which can outperform the market. To examine this question, I sort firm-quarter observations with repurchases into twenty equally-sized bins based on the fraction of shares repurchased, and do the same for issuances. I regress 2-year stock returns on indicator variables for these 5-percentile bins of repurchases and issuances for common stocks of U.S. firms from 2003-2017. Similar to the results in Chapter 1, I find only large issuances significantly predict future stock returns in this restricted sample. Firms making issuances larger than 4.18% of their shares outstanding experience lower 2-year returns of 13.2%. Share repurchases and smaller share issuances do not predict stock returns in this restricted sample.

Using these findings, I examine whether the predictive effect of large issuances can be used to construct portfolios which outperform the market after 2003. I first construct a portfolio which short-sells firms that have made a 1-quarter issuance greater than 4.18% of their shares outstanding in the past year. The proceeds from the short-sale are invested in the market portfolio. Following the methodology of Alexander (2000), the initial capital of this fund is invested in the risk-free bond. Since many investors are not permitted or choose not to engage in short sales, I also construct a long-only portfolio which invests in companies that have not made issuances larger than 1.35% in the past year. I find the short-sale strategy generates significant monthly excess returns of 0.61% using an equal-weight approach and 0.32% using a value-weight approach. The long-only portfolio generates significant monthly excess returns of 0.31% using an equal-weight approach and 0.05% using a value-weight approach. These results are largely robust when adding transaction costs, although the value-weighted long-only portfolio no longer generates significant excess returns when it faces a one-way transaction cost of 0.5% on the purchase and sale of stocks. Overall, the performance of these portfolios provide evidence that large share issuances still predict future returns after 2003.

This paper is motivated by previous studies on the predictive effects of share repurchases and issuances. Daniel and Titman (2006) and Pontiff and Woodgate (2008) find that changes in shares outstanding are negatively correlated with future 1- to 4-year returns from 1975-2002. In Chapter 1, I show this relationship is non-linear; while most repurchases predict higher returns and large issuances predict lower returns, small issuances also predict higher returns. These findings are supported by papers examining announcements of share repurchases and issuances over this time period. Several papers found firms that announced repurchases had higher returns (e.g. Ikenberry et al. (1995), Peyer and Vermaelen (2009)) and firms that announced senior equity offerings experienced lower returns (Loughran and Ritter (1995), Spiess and Affleck-Graves (1995), Ritter (2003)) in the years following the announcement during the 1975-2002 time-frame.

Fu and Huang (2016) find these relationships weakened after 2003. They show announcements of repurchases and issuances no longer predicted future returns from 2003-2013. While changes in shares outstanding were still negatively correlated with returns, the coefficient became much smaller in magnitude. In Chapter 1, I examine the effect of repurchases and issuances non-linearly and find that while large issuances still predict lower returns after 2003, repurchases and small issuances no longer predicted significantly higher returns.[1] These papers include all stocks traded on the NYSE and NASDAQ exchanges in their sample, including those of non-U.S. firms, closed-end funds, and investment trusts. This paper restricts the analysis to US-based firms that are not investment funds or trusts to be more relevant to investors who don't invest in these products, and finds the previous results are robust to this subsample.

Section 2.2 examines the returns of the buyback ETFs. In Section 2.3, I describe and perform the binned regressions. I construct the issuance portfolios and compare their returns to the market return in Section 2.4. Section 2.5 concludes.

2.2 Performance of Buyback ETFs

To examine whether portfolios constructed using repurchase information can outperform the market portfolios, I first consider whether the ETFs which invest in US firms that make share repurchases outperform the market. There are two such ETFs in existence as of 2020. The Powershares/Invesco Buyback Achievers ETF (ticker: PKW) was launched in January 2007. This ETF tracks the NASDAQ US Buyback Achievers Index, a value-weight index of US corporations which have reduced shares outstanding by 5% or more over the previous 12 months. The SPDR S&P 500 Buyback ETF (ticker: SPYB) was launched in March 2015. This ETF tracks the equal-weight performance of the 100 companies in the S&P 500 index which had the largest share buyback ratios over the past 12 months. I compare these portfolios to the CRSP market portfolios using the Sharpe (1994) Ratio and the calendar-time approach of Mitchell and Stafford (2000). Neither method finds evidence these repurchase ETFs outperformed the market, which is consistent with the findings of Fu and Huang (2016) and the findings in Chapter 1.

[1]The coefficient on small issuances was significant, but only at the 10% level.

2.2.1 Data and Summary Statistics

I examine the monthly holding period returns of the Powershares/Invesco Buyback Achievers ETF and the SPDR S&P 500 Buyback ETF in the CRSP database starting from their launch dates to December 2019. Table 2.1 compares the excess returns of these ETFs over the risk-free rate against those of the market portfolio (represented by the CRSP value-weighted portfolio) since their inception.

Table 2.1: Summary statistics of buyback ETF returns

	Mean	SD	N
Buyback Achievers ETF			
Excess Return	0.0077	0.0454	156
Market Excess Return	0.0074	0.0434	156
SPDR Buyback ETF			
Excess Return	0.0076	0.0431	58
Market Excess Return	0.0087	0.0355	58

Notes: This table compares the monthly excess returns over the risk-free rate of the Powershares/Invesco Buyback Achievers ETF (PKW) and the SPDR S&P 500 Buyback ETF (SPYB) to the excess returns of the market, represented by the CRSP value-weight portfolio.

The summary statistics displayed in Table 2.1 show neither fund noticeably outperformed the market. The mean excess return of the SPDR Buyback ETF was lower than that of the market by 0.09% per month since its inception. The 0.77% monthly return of the Powershares/Invesco Buyback Achievers ETF was very similar to that of the market portfolio at 0.74% per month.

These statistics can be used to compute the Sharpe (1994) Ratio, which is a measure of risk-adjusted excess return of a portfolio. The Sharpe Ratio is the mean excess return over the risk-free rate divided by standard deviation of the excess return. The Sharpe Ratio of the Buyback Achievers ETF is 0.169, which is sightly lower than the Sharpe Ratio of the market of 0.171 over the same period. The Sharpe Ratio of the SPDR Buyback ETF is 0.177, which is also lower than the market's Sharpe Ratio of 0.244 over the same period. Neither the excess returns or the Sharpe Ratios of these two ETFs provide evidence suggesting that a portfolio of repurchasing companies outperformed the market.

2.2.2 Calendar-Time Portfolio Regressions

While the Sharpe Ratio accounts for risk using the standard deviation of returns, it doesn't consider the portfolio's correlation with specific risk factors. For example, a portfolio may generate positive abnormal returns even with below-market mean returns if its returns are negatively correlated with (and thus provides insurance against) one or more risk factors. I use the calendar-time approach of Mitchell and Stafford (2000) to estimate a portfolio's abnormal returns after accounting for its correlation with risk factors.

With the calendar-time approach, the portfolio's excess return over the risk-free rate is regressed on the Fama and French (1993) and Carhart (1997) risk factors:

$$R_{p,t} - r_{f,t} = a_p + b_p(R_{m,t} - r_{f,t}) + s_p SMB_t + h_p HML_t + m_p UMD_t + e_{p,t} \tag{2.1}$$

For month t, $R_{p,t}$ is the portfolio return, $r_{f,t}$ is the risk-free return, $R_{m,t}$ is the return of the market portfolio, SMB_t is the excess return of the portfolio of low-size firms over the portfolio of large-size firms, and HML_t is the excess return of the portfolio of high book-to-market firms over the portfolio of low book-to-market firms. UMD_t is the Carhart (1997) momentum factor, which is the excess return of firms with the highest prior-12 month return over firms with the lowest prior-12 month return. The constant a_p is the variable of interest and measures the abnormal return of the portfolio when controlling for these risk factors. If a_p is positive (negative) and significant, the portfolio outperformed (underperformed) the market after controlling for risk factors.

The calendar-time regressions show neither the Powershares/Invesco Buyback Achievers ETF (PKW) or the SPDR S&P 500 Buyback ETF (SPYB) have significant abnormal returns when controlling for the Fama-French risk factors (see Table 2.2). Overall, the performance of these ETFs provide no evidence that share repurchase information could be used to construct portfolios that outperformed the market during the 2003-2019 period.

Table 2.2: Abnormal returns of buyback ETFs

	PKW	PKW	SPYB	SPYB
Constant	0.0006	0.0007	-0.0016	-0.0012
	(0.0012)	(0.0012)	(0.0018)	(0.0018)
MKT-RF	0.981***	0.961***	1.149***	1.096***
	(0.0438)	(0.0437)	(0.0432)	(0.0521)
SMB	0.0465	0.0459	0.0400	0.0267
	(0.0486)	(0.0474)	(0.0603)	(0.0599)
HML	0.0796	0.0309	0.239**	0.0128*
	(0.0529)	(0.0535)	(0.0600)	(0.0681)
UMD		-0.0701**		-0.139**
		(0.0228)		(0.0655)
R^2	0.923	0.927	0.926	0.935
N	156	156	58	58

Notes: This table shows the results of the calendar-time regressions for the repurchase ETFs using monthly returns. PKW is the Powershares/Invesco Buyback Achievers ETF, and SPYB is the SPDR S&P 500 Buyback ETF. The constant is the variable of interest and represents the estimated abnormal returns of the portfolio when controlling for the Fama and French (1993) and Carhart (1997) risk factors. MKT-RF is the excess return of the CRSP value-weight market portfolio over the risk-free rate. SMB is the excess return of small firms over large firms. HML is the excess return of firms with high book-to-market ratios over firms with low book-to-market ratios. UMD is the return of firms with high returns over firms with low returns.

2.3 Effect of Repurchases and Issuances, 2003-2017

In this section, I examine whether there are strategies around repurchases and issuances that can be used to generate above-market returns using data from 2003-2017. While Fu and Huang (2016) find the predicted effect of repurchases and issuances shrinks greatly after 2003, the analysis in Chapter 1 finds large issuances still predict significantly negative returns in the 2003-2017 time period. Both of these previous studies included all stocks in the CRSP database in their samples including as those of American depository receipts and various types of exchange-traded funds. Many investors may choose not to or may not be allowed to invest in these stocks. For example, most mutual funds do not invest in other funds, and some mutual funds only invest in stocks of US firms. Because the repurchase and issuance behavior of these exchange-traded entities may differ from that of US firms, the inclusion of these stocks could make the results of these previous studies less relevant for such investors.

In this section, I regress 2-year stock returns on 5-percentile repurchase and issuance bins with the restricted subsample of common stocks of US-based companies. I find the main results from Chapter 1 holds in the subsample. Repurchases and small issuances do not predict higher returns from 2003 to 2017, but large issuances do predict significantly lower returns. This finding suggests it may be possible to construct outperforming portfolios with issuance information during this period.

2.3.1 Data and Summary Statistics

The sample for this analysis consists of common stocks of all US-based firms traded on the NYSE, AMEX, ArcaEx, and NASDAQ exchanges in both the CRSP and Compustat databases from 2003-2017. These stocks must have a share code 10 or 11 in CRSP, which represent common stocks of U.S. firms. Observations must have non-missing return, price, and shares outstanding data to be included in the sample. A quarterly time step is used in this sample, which reflects the reporting period of the Compustat database. This sample contains 211,908 firm-quarter observations across 7,076 firms.

Table 2.3 shows the distribution of share codes in the CRSP monthly stock database from 2003-2017 with non-missing return, price, and shares outstanding data. Stocks with share code 11 in CRSP are ordinary common shares which need not be further defined and make up 62% of the sample. Stocks with share code 10 are ordinary common shares which have not been further defined and only represent 0.02% of the sample. Other types of stocks in the CRSP database include stocks of companies incorporated outside the U.S. (share code 12), closed end funds (share codes 14, 44, 74, and 75), real estate investment trusts (share code 18), and American depository receipts (share codes 30 and 31).

Using the restricted sample, I construct variables for 2-year cumulative excess returns over the CRSP equal-weight portfolio, 1-quarter changes in shares outstanding, size, book-to-market, and the prior 6-month return as a proxy for momentum.[2] 1-quarter changes in shares outstanding are constructed as the percent change in shares outstanding and are adjusted to remove the effect

[2] See Appendix B.1 for details on the construction of these variables.

Table 2.3: Descriptions and frequencies of share codes

Code	Freq.	Percent	Description	
10	52	0.02	Ordinary Common Shares	Securities which have not been further defined
11	212,040	62.47	Ordinary Common Shares	Securities which need not be further defined
12	18,116	5.34	Ordinary Common Shares	Companies incorporated outside the US
14	17,865	5.26	Ordinary Common Shares	Closed-end funds
15	60	0.02	Ordinary Common Shares	Closed-end fund companies incorporated outside the US
18	7,893	2.33	Ordinary Common Shares	Real Estate Investment Trusts
21	106	0.03	Certificates	Securities which need not be further defined
30	28	0.01	American Depository Receipts	Securities which have not been further defined
31	17,615	5.19	American Depository Receipts	Securities which need not be further defined
41	118	0.03	Shares of Beneficial Interest	Securities which need not be further defined
44	15,350	4.52	Shares of Beneficial Interest	Closed-end funds
48	1,994	0.59	Shares of Beneficial Interest	Real Estate Investment Trusts
71	4,752	1.4	Units	Securities which need not be further defined
72	423	0.12	Units	Companies incorporated outside the US
73	42,283	12.46	Units	Americus Trust Components (Primes and Scores)
74	683	0.2	Units	Closed-end funds
75	66	0.02	Units	Closed-end fund companies incorporated outside the US

of stock splits. To construct the 2-year cumulative excess returns, I sum the monthly excess returns over the CRSP equal-weight portfolio over the two years as opposed to using the two-year multiplicatively-compounded buy-and-hold returns.[3] While this doesn't reflect the returns for an investor who buys and holds the stock, it avoids the econometric issues around skewness and multiplicative compounding documented by Fama (1998). All variables are winsorized at the 1% and 99% levels.

The summary statistics of these variables are similar to the summary statistics when all share codes are included in the sample.[4] A major difference between the subsample and the full sample with all share codes is that the variation of changes in shares outstanding is larger when stocks of all share codes are included. The repurchase and issuance centiles of these samples (see Table 2.4) show that despite stocks of other share codes accounting for only 28% of observations with repurchases and issuances, they are make up a large fraction of the largest repurchases and issuances. The mean repurchase is 64% smaller and the mean issuance is 56% when excluding these stocks, and the largest percentile of repurchases and issuances are 72% and 51% smaller,

[3]This is the same returns metric as the one used in Chapter 1.
[4]See Appendix B.2 for the summary statistics and contemporaneous correlations of all variables.

respectively. The repurchase and issuance behavior of stocks with other share codes are different from those of common stocks of US firms. As such, the inclusion of these stocks could significantly affect the estimated relationship between stock returns and share repurchases and issuances.

Table 2.4: Repurchase and issuance centiles (excl. zeroes), 2003-2017

Centile	25	50	75	90	95	99	Mean	SD	N
Share codes 10 & 11									
Repurchase	0.002	0.007	0.017	0.035	0.053	0.123	0.015	0.024	48437
Issuance	0.001	0.003	0.010	0.042	0.130	0.489	0.024	0.079	134743
Other share codes									
Repurchase	0.016	0.053	0.129	0.250	0.353	0.609	0.098	0.123	22380
Issuance	0.004	0.038	0.154	0.393	0.671	2.333	0.158	0.345	49971
All share codes									
Repurchase	0.003	0.011	0.037	0.111	0.200	0.441	0.040	0.076	70886
Issuance	0.001	0.005	0.024	0.152	0.297	1.000	0.056	0.151	184967

Notes: This table compares the centiles of repurchases and issuances between common stocks of US-based firms which are not closed-end funds or investment trusts (share codes 10 & 11) to those of stocks with other share codes and of all stocks in the CRSP and Compustat databases. Observations with zero repurchases are excluded when calculating repurchase centiles, and observations with zero issuances are excluded when calculating issuance centiles. Repurchase is one-quarter percent decreases in shares outstanding. Issuance is one-quarter increases in shares outstanding.

2.3.2 Analysis

I conduct the binned panel regressions with Driscoll and Kraay (1998) standard errors from Chapter 1 on the 2003-2017 sample including only stocks with share codes 10 and 11 in CRSP. Firm-quarter observations with repurchases are sorted into twenty 5-percentile bins based on their magnitude, and the same is done for firm-quarter observations with issuances. Each repurchase bin contains roughly 2,100 observations and each issuance bin contains roughly 5,926 observations. I run a panel regression of 2-year excess returns over the CRSP equal-weight portfolio on indicator

Table 2.5: Contemporaneous correlations, share codes 10-11, 2003-2015

	ChangeShares	RepurchaseIND	IssuanceIND	Repurchase	Issuance
Return	-0.053	0.009	-0.025	0.003	-0.058
Size	-0.091	0.223	0.033	-0.059	-0.111
BTM	-0.041	-0.012	-0.127	0.025	-0.018
MissBTM	0.037	-0.032	0.019	0.024	0.038
Momentum	0.057	-0.066	0.093	-0.018	0.034

Notes: This table displays the contemporaneous correlations between changes in shares outstanding, repurchase, and issuance variables and the other main variables for stocks with share code 10 or 11. Correlations displayed for the Repurchase and Issuance variables are calculated excluding observations with zero repurchases and issuances, respectively. Return is the 2-year cumulative stock return: the sum of the monthly holding period returns over the next 24 months. ChangeShares is the one-quarter percent change in shares outstanding. RepurchIND and IssuanceIND are indicator variables that take on a value of 1 if the observation contained a repurchase or issuance, respectively. Repurchase is one-quarter percent decreases in shares outstanding. Issuance is one-quarter increases in shares outstanding. Size is the log of the market capitalization. BTM is the book-to-market ratio: the log of the book value of common equity divided by the market capitalization. The correlations for BTM are calculated excluding observations with missing BTM values. MissBTM is the missing book-to-market indicator variable, which takes on a value of 1 if BTM is missing and is set to 0 otherwise. Momentum is the prior 6-month buy-and-hold return.

variables for the repurchase and issuance bins, controlling for size, book-to-market, and momentum:[5]

$$ExReturn_{i,t+1,t+24} = \alpha + \beta_1 RepurchaseBins_{i,t} + \beta_2 IssuanceBins_{i,t} + \gamma_1 FirmControls_{i,t} + \epsilon_{i,t} \tag{2.2}$$

I find very similar results to those of Chapter 1 (see Figure 2.1). Large one-quarter share issuances predict significantly lower 2-year returns. Firms that issued more than 4.2% of their shares outstanding in one quarter experienced lower returns of 13.2% over two years. These represent the largest 10% of issuances. I find no evidence repurchases or small issuances provide information on future returns. These results are qualitatively similar to those of Chapter 1, which found only large issuances had a significant effect at the 5% level in the post-2003 subsample with stocks of all share codes. However, the magnitude of the coefficients for small repurchases and issuances are much closer to 0 with the restricted sample compared to when all share codes are included.

To further examine the effect of limiting the sample to common stocks of US firms, I re-run the binned regressions on a sample which only contains stocks with share codes other than

[5] See Appendix B.1 for how these variables are constructed.

10 or 11. This sample includes common stocks of non-US firms, certificates, and closed-end funds. The results of this regression are shown in Figure 2.2. Overall, these results are similar to those of common stocks of US firms. Small repurchases and issuances predict an insignificantly higher return and large issuances predict a significantly lower return. The predicted effect of large repurchases differs. Here, the largest repurchases are predicted to have an insignificant negative effect. One factor that may be causing this difference is a difference in the variability of share repurchases between the two samples. As discussed in Section 2.3.1, the variance of repurchases and issuances is larger for stocks that do not have share codes 10 or 11. Chapter 1 finds the largest repurchases predict lower returns than small repurchases, which could explain this difference in results.

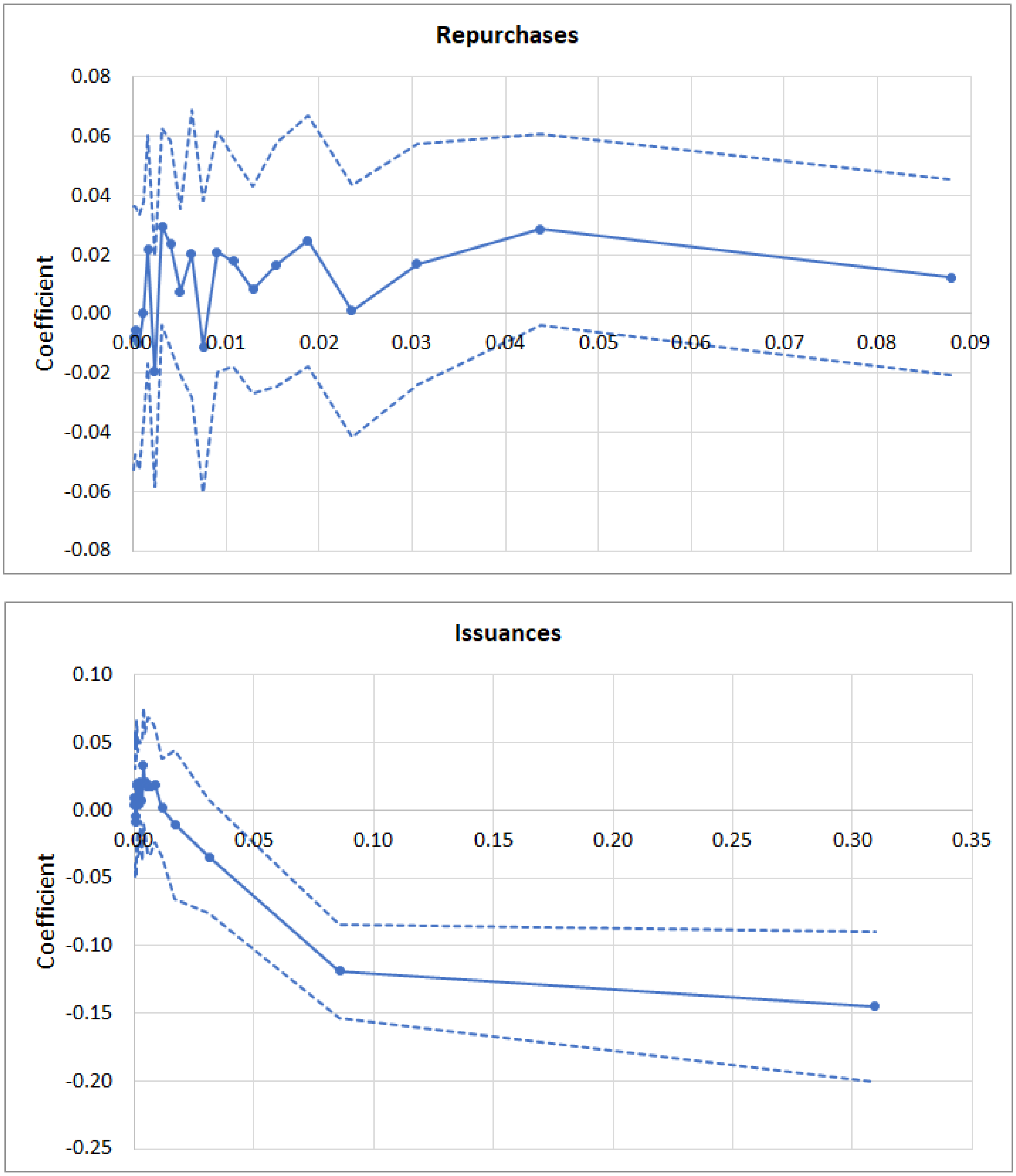
This analysis indicates the findings of Fu and Huang (2016) and Chapter 1 are largely robust when the sample is restricted to the common stocks of US firms. It reinforces the earlier finding that the predicted effect of repurchases and issuances shrink in the 2003-2017 period, but unlike Fu and Huang (2016), it finds large issuances continue to predict returns in this period.

Table 2.6: Binned regression, 2003-2017: coefficients of firm controls

	Common	Other
Size	0.0031	0.0027
	(0.0055)	(0.0038)
BTM	0.0354***	0.0106***
	(0.0129)	(0.0038)
MissBTM	-0.0239	-0.057**
	(0.0414)	(0.0217)
Momentum	0.0019	0.0704*
	(0.0395)	(0.0397)
Constant	0.0482	-0.0122
	(0.0414)	(0.0274)
R^2	0.0054	0.0124
N	211908	127124

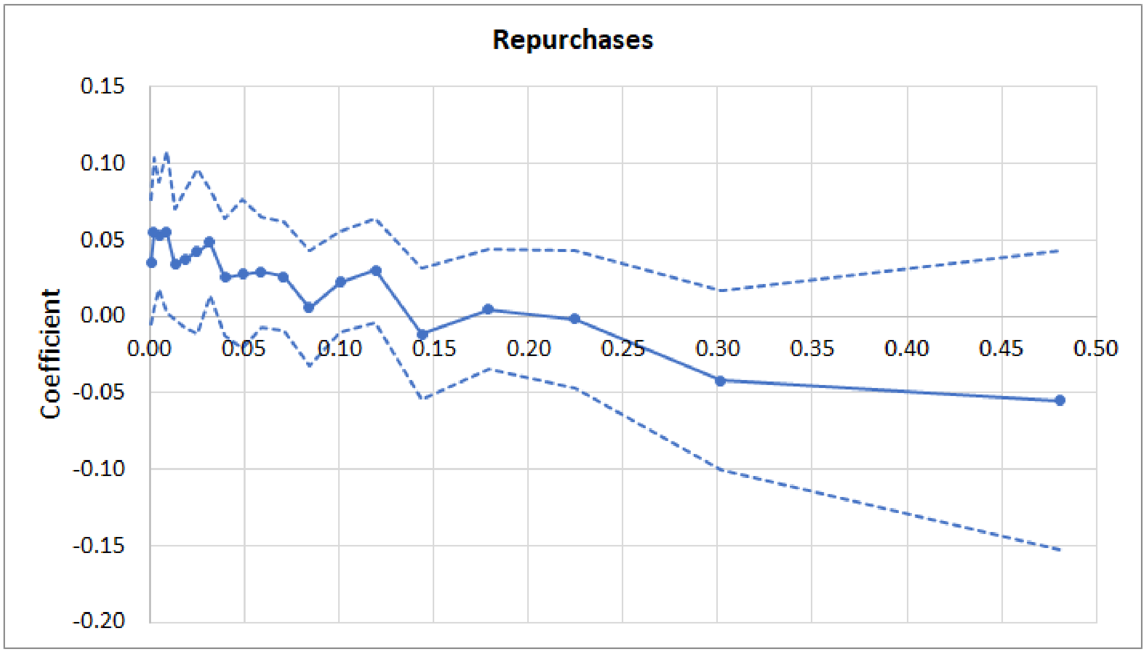
Notes: This table displays the coefficients of the firm controls for the binned regression. See Figure 2.1 or Table B.3 in Appendix B.3 for the coefficients on repurchase and issuance bins for common stocks of US firms (share codes 10 and 11). See Figure 2.2 or Table B.4 in Appendix B.3 for the coefficients on repurchase and issuance bins for stocks with other share codes. Size is the log of the market capitalization. BTM is the book-to-market ratio: the log of the book value of common equity divided by the market capitalization. MissBTM is the missing book-to-market indicator variable, which takes on a value of 1 if BTM is missing and is set to 0 otherwise. Momentum is the prior 6-month buy-and-hold return.

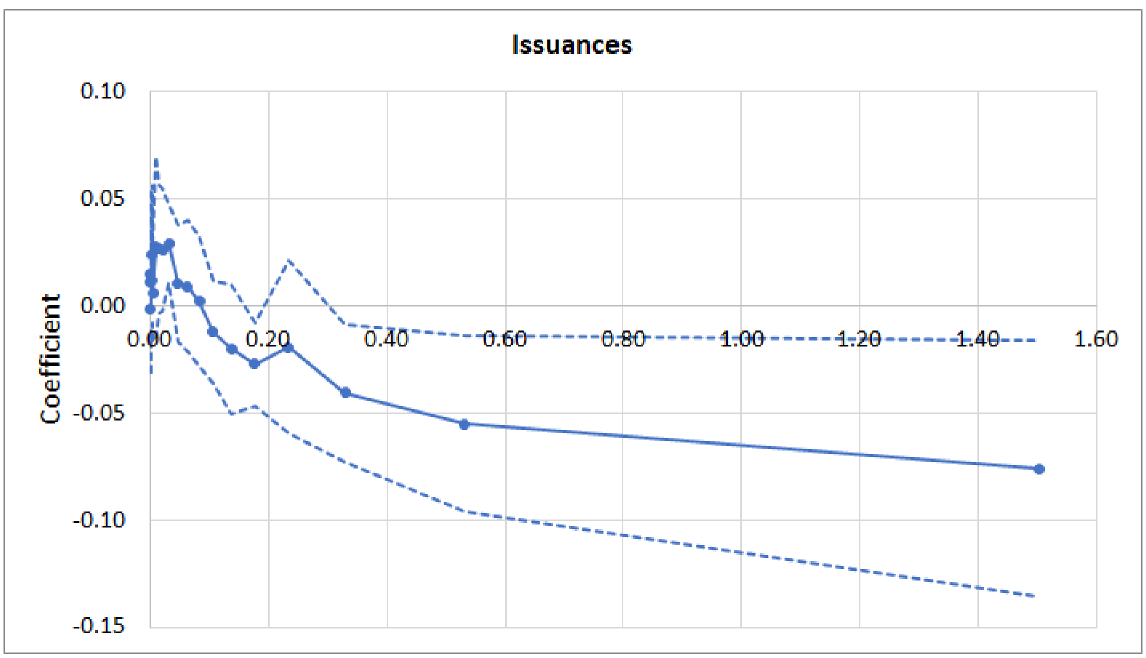
Figure 2.1: Binned regression, share codes 10-11, 2003-2017: coefficients of repurchase/issuance bins



Notes: This figure graphs the coefficients on the 5-percentile repurchase and issuance bins from the binned regression. The horizontal axis is the fraction of shares outstanding repurchased or issued. The circular markers on the solid line represents the mid-point fraction of shares outstanding of the range of each 5-percentile bin. The dashed lines represent the 95-percent confidence interval. See Appendix B.3 for the numerical values of these coefficients.

Figure 2.2: Binned regression, share codes 12-75, 2003-2017: coefficients of repurchase/issuance bins





Notes: This figure graphs the coefficients on the 5-percentile repurchase and issuance bins from the binned regression on stocks with share codes 12-75. The horizontal axis is the fraction of shares outstanding repurchased or issued. The circular markers on the solid line represents the mid-point fraction of shares outstanding of the range of each 5-percentile bin. The dashed lines represent the 95-percent confidence interval. See Appendix B.3 for the numerical values of these coefficients.

2.4 Issuance Portfolios

The analysis in Section 2.3 found large issuances predict lower 2-year returns. In this section, I construct two portfolios to examine whether investors can exploit this finding to make above-market risk-adjusted returns. The first portfolio short-sells stocks of firms who make large issuances, and the second portfolio invests in firms who do not make large issuances. I back-test the performance of these two portfolios using 2003-2019 data and find evidence these portfolios both outperformed the market, even when transaction costs are considered.

2.4.1 Portfolio Construction and Summary Statistics

I construct two portfolios to test whether the underperformance of firms who make large issuances can be used by investors to generate excess risk-adjusted returns. The first portfolio short-sells firms which made a 1-quarter issuance greater than 0.0418 in the past 12 months.[6] This threshold chosen is the lower bound of the first 5-percentile issuance bin where the coefficient on returns is significantly negative in the regressions from Section 2.3.2. The proceeds from the short-sales are used to buy the market portfolio. The fund's initial capital must also be considered as it is not used for the short-sale or to buy the market portfolio. I follow the methodology in Alexander (2000), where the initial capital is invested in the risk-free bond for use as collateral. As such, this portfolio generates returns equal to:

$$r_{1,t} = r_f + r_m - r_{ss} \tag{2.3}$$

where $r_{1,t}$ is the return of the short-sale portfolio, r_f is the risk-free return, r_m is the market return, and r_{ss} is the return of the stocks which are sold short. The value-weighted CRSP market portfolio is used for r_m for the value-weight short-sale portfolio, and the equal-weighted CRSP market portfolio is used for r_m for the equal-weight short-sale portfolio.

Because short-selling exposes investors to unlimited downside risk, many investors are not allowed to or choose not to short-sell. The second portfolio tests whether the underperformance of

[6]The number of stocks matching this criteria each month ranges from 598 to 1355 in the study period. There were no periods where no stocks matched this criteria.

firms who make large issuances can be used to outperform the market without short-selling. This portfolio invests in stocks of all US firms listed in the NYSE and NASDAQ exchanges which did not make a 1-quarter issuance greater than 1.35% over the past 12 months. The binned regression in Section 2.3.2 finds a negative coefficient on returns for firms issuing more than 1.35% of their shares, but the lower returns are not significant until the issuances exceed 4.18%. This lower threshold was chosen to exclude a greater number of stocks and thus generate a larger difference compared to the market portfolio.

For each of these portfolios, I calculate their returns with and without transaction costs. I follow the methodology outlined in Alexander (2000) to calculate the returns of the short-sale portfolio with transaction costs. A haircut of 0.021% per month is deducted from returns to represent the costs of borrowing stocks to short-sell. Additionally, the investor must provide additional collateral of 30% of the value of the initial investment which will be invested in risk-free bonds. As such, the returns with transaction costs for the short-sale portfolio is:

$$r_{1c,t} = r_f + (r_m - r_{ss} - 0.021)/1.3 \tag{2.4}$$

where $r_{1c,t}$ is the return on the short-sale portfolio with transaction costs in month t, r_f is the risk-free return, r_m is the market return, and r_{ss} is the return of the stocks which are sold short. Again, the value-weighted CRSP market portfolio is used for r_m for the value-weight short-sale portfolio, and the equal-weighted CRSP market portfolio is used for r_m for the equal-weight short-sale portfolio.

For the long portfolio, I assume transaction costs are proportional to the value of stocks purchased or sold. Based on Keim and Madhavan (1997) and Busse et al. (2016), I use one-way transaction costs of 0.5%. For each stock, this transaction cost is paid on the difference between the value of the stock held at the end of the previous period and the value of the stock held at the beginning of the current period. The transaction cost for stock i and month t is:

$$c^l_{i,t} = 0.005 * \left| w_{i,t} - w_{i,t-1} \frac{\text{mktcap}_{i,t}}{\text{mktcap}_{i,t-1}} \frac{1}{(1 + r_{2,t-1})} \right| \tag{2.5}$$

where $c^l_{i,t}$ is the transaction cost paid on buying or selling stock i in month t, $w_{i,t}$ is the portfolio weight of stock i in month t, $\text{mktcap}_{i,t}$ is the market capitalization of stock i in month t, and $r_{2,t-1}$ is the prior month's return on the long portfolio without transaction costs. The last term in the equation represents the portfolio weight of the stock at the end of the prior period assuming the portfolio participates proportionally in any share repurchases or issuances.

Table 2.7: Summary statistics of issuance portfolios

	w/o transaction costs			with transaction costs				
	mean	std.dev.	Sharpe	mean	std.dev.	Sharpe	cost	N
Short-Sale Portfolios								
Equal-Weight	0.0047	0.0225	0.2087	0.0027	0.0172	0.1541	0.0020	204
Value-Weight	0.0021	0.0215	0.0999	0.0007	0.0165	0.0419	0.0015	204
Long-Only Portfolios								
Equal-Weight	0.0125	0.0499	0.2500	0.0118	0.0499	0.2357	0.0007	204
Value-Weight	0.0094	0.0379	0.2474	0.0092	0.0379	0.2420	0.0002	204
Market Portfolios								
CRSP Equal-Weight	0.0097	0.0480	0.2017					204
CRSP Value-Weight	0.0089	0.0402	0.2208					204
S&P 500	0.0072	0.0387	0.1850					204

Notes: This table shows the average return, standard deviation, and Sharpe ratios of the equal-weight and value-weight short-sale portfolios, long-only portfolios, and market portfolios from January 2003 to December 2019. Figures with and without transaction costs are provided for the short-sale and long-only portfolios. The average transaction cost (cost) is calculated as the difference between the mean returns of the portfolios with and without transaction costs.

Table 2.7 shows the summary statistics of the portfolios. The mean return and Sharpe ratio of the short-sale portfolios provide no evidence that it outperforms the market. Even without considering transaction costs, the average return of the equal-weight and value-weight short-sale portfolios are lower than the returns of the respective market portfolios. The short-sale portfolios have a lower standard deviation of returns, but not enough to generate higher Sharpe ratios than the market portfolios.

In contrast, the long-only portfolios generated greater average returns than the market portfolio even with transaction costs. These long-only portfolios have similar standard deviations to the market portfolios, and thus have higher Sharpe ratios. While these metrics don't account for the correlation between this portfolio's returns and those of risk factors, it suggests issuance information can be used to create portfolios which outperform the market.

The difference in mean monthly returns between the portfolios with and without transaction costs can be used to calculate the average transaction costs paid by each portfolio. The equal-weight portfolios required higher transaction costs to construct than their value-weight counterparts. For the long-only portfolios, the monthly rebalancing of the equal-weight portfolio necessitated more transactions. The equal-weight long-only portfolio averaged a monthly turnover of 7% compared to the 2% turnover of the value-weight portfolio.[7] The equal-weight short-sale portfolio also generates higher transaction costs. There are no variable transaction costs for the short-sale portfolio, but the collateral requirement has a larger effect on a portfolio with higher mean returns.

With the exception of the value-weight long-only portfolio, these monthly average transaction costs are similar to those faced by mutual funds. Busse et al. (2016) find the highest quintile of mutual funds experienced trading costs averaging 0.14% per month while the lowest quintile averaged 0.09% per month. The short-sale portfolios experienced trading costs on the high-end of this range, which is expected due to the additional regulations and collateral requirements around short-selling (Alexander, 2000). In contrast, the value-weight long-only portfolio experiences very low trading costs due to its low turnover.

2.4.2 Calendar-Time Approach

The higher mean return of the long-only portfolios identified in Section 2.4.1 may be due to exposures to risk factors, and the short-sale portfolios could be a desirable investment despite its low average return if it provides insurance against risk factors. As in Section 2.2.2, I use the calendar-time approach to assess these portfolios' abnormal returns over the risk-free rate when controlling for the Fama and French (1993) and Carhart (1997) factors.

All portfolios considered have positive and significant abnormal returns when transaction costs are not considered (see Table 2.8). Interestingly, the abnormal returns of the short-sale portfolios

[7] For comparison, Busse et al. (2016) find large mutual funds had an average monthly turnover of roughly 6% and small mutual funds had turnover of roughly 10% from 1999-2011.

is larger than the abnormal returns of the respective long-only portfolios even though the excess returns of the short-sale portfolios are lower (as discussed in Section 2.4.1). The returns of the short-sale portfolios are negatively correlated with and thus provide insurance against the market return and size risk factors.

Table 2.8: Calendar-time regressions of issuance portfolios without transaction costs

	Short EW	Short VW	Long EW	Long VW
Constant	0.0061***	0.0032**	0.0031***	0.0005**
	(0.0011)	(0.0014)	(0.0006)	(0.0002)
MKT-RF	-0.215***	-0.24***	0.918***	0.962***
	(0.0321)	(0.0491)	(0.0216)	(0.0067)
SMB	-0.479***	-0.112*	0.678***	-0.0455***
	(0.052)	(0.062)	(0.033)	(0.0117)
HML	0.0903*	-0.0991	0.137***	-0.0119
	(0.0498)	(0.106)	(0.0472)	(0.0124)
UMD	0.0606**	0.0437	-0.189***	0.006
	(0.0263)	(0.0439)	(0.0241)	(0.0078)
R^2	0.558	0.344	0.971	0.993
N	204	204	204	204

Notes: This table displays the results of the calendar-time regressions for the issuance portfolios without transaction costs. The excess return of the short-sale portfolio is the return of the market portfolio minus the return of stocks with large issuances. The excess return of the long-only portfolio is the return of non-large-issuers minus the risk-free rate. The constant is the variable of interest and represents the estimated abnormal returns of the portfolio when controlling for the Fama and French (1993) and Carhart (1997) risk factors. MKT-RF is the excess return of the CRSP value-weight market portfolio over the risk-free rate. SMB is the excess return of small firms over large firms. HML is the excess return of firms with high book-to-market ratios over firms with low book-to-market ratios. UMD is the return of firms with high returns over firms with low returns.

The results in Table 2.9 show these findings are robust to transaction costs with one exception. When transaction costs are included, the abnormal returns of the value-weight long-only portfolio become insignificant. Despite having low monthly transaction costs due to its low turnover rate, the costs are enough to eliminate the portfolio's abnormal returns since its abnormal returns without transaction costs are already very low. The transaction costs represent a third of those abnormal returns. The other portfolios still generate abnormal returns even with transaction costs. The existence of portfolios which outperform the market using issuance information even after transaction costs are considered shows that large share issuances still provide information on future stock returns in the 2003-2019 period.

The equal-weight portfolios continue to significantly outperform the value-weight portfolios

Table 2.9: Calendar-time regressions of issuance portfolio with transaction costs

	Short EW	Short VW	Long EW	Long VW
Constant	0.0046***	0.0023**	0.0024***	0.0003
	(0.0008)	(0.0011)	(0.0006)	(0.0002)
MKT-RF	-0.165***	-0.185***	0.919***	0.962***
	(0.0247)	(0.0377)	(0.0216)	(0.0067)
SMB	-0.368***	-0.0862*	0.676***	-0.046***
	(0.04)	(0.0477)	(0.0329)	(0.0118)
HML	0.0695*	-0.0762	0.138***	-0.0122
	(0.0383)	(0.0819)	(0.0471)	(0.0125)
UMD	0.0466**	0.0336	-0.189***	0.0062
	(0.0202)	(0.0338)	(0.024)	(0.0078)
R^2	0.558	0.344	0.971	0.993
N	204	204	204	204

Notes: This table displays the results of the calendar-time regressions for the issuance portfolios with transaction costs. The excess return of the short-sale portfolio is the return of the market portfolio minus the return of stocks with large issuances. The excess return of the long-only portfolio is the return of non-large-issuers minus the risk-free rate. The constant is the variable of interest and represents the estimated abnormal returns of the portfolio when controlling for the Fama and French (1993) and Carhart (1997) risk factors. MKT-RF is the excess return of the CRSP value-weight market portfolio over the risk-free rate. SMB is the excess return of small firms over large firms. HML is the excess return of firms with high book-to-market ratios over firms with low book-to-market ratios. UMD is the return of firms with high returns over firms with low returns.

after controlling for the size and momentum risk factors. Edwards et al. (2018) explores several reasons why equal-weight portfolios outperform value-weight portfolios. Equal-weight portfolios overweight small firms compared to value-weight portfolios, and small firms tend to generate higher returns than large firms (Banz, 1981). Equal-weight portfolios also underweight stocks that had higher past returns, and stocks tend to experience mean reversion in returns (Carhart, 1997). However, both of these reasons should be controlled for by the Fama and French (1993) and Carhart (1997) factors.[8] This finding suggests the predicted effect of large issuances on returns are especially strong for small-capitalization stocks or stocks which had low recent returns.

[8]For example, the abnormal return of the CRSP equal-weight market portfolio is not significantly different from that of the CRSP value-weight portfolio when controlling for these risk factors. Neither portfolio generates statistically-significant abnormal returns.

2.5 Conclusion

In this paper, I examine whether information on share repurchases and issuances can be used to construct portfolios that outperform the market in the 2003-2019 time period. I find no evidence that share repurchases can be used to construct outperforming portfolios, either through the returns of repurchase ETFs or through a binned regression on common stocks of U.S. firms in the CRSP and Compustat databases. The binned regression suggests the stocks of large issuers still experience lower returns during this time period. I construct two portfolios which exploit the lower return of large issuers and show they generate positive abnormal returns after controlling for risk factors and transaction costs. These findings suggest investors can use information from share issuances to construct portfolios which outperformed the market in the 2003-2019 period.

Chapter 3

Delegated Investment Management and Boom-Bust Cycles

3.1 Introduction

> Alpha is quite hard to generate since most ways of doing so depend on the investment manager possessing unique abilities [...] How then can untalented investment managers justify their pay? Unfortunately, all too often it is by creating fake alpha – appearing to create excess returns but in fact taking on hidden tail risks, which produce a steady positive return most of the time as compensation for a rare, very negative, return [...] An investment manager who bought AAA-rated tranches of collateralised debt obligations (CDO) [prior to the 2007 financial crisis] generated a return of 50 to 60 basis points higher than a similar AAA-rated corporate bond. That "excess" return was in fact compensation for the "tail" risk that the CDO would default. (Rajan, 2008)

The 2007 financial crisis was triggered by sharp and severe losses in mortgage-backed securities following declines in housing prices and an increase in mortgage defaults. The popularity of mortgage-backed securities in the years preceding the financial crisis coincided with a boom in investment funds. Assets under management by mutual funds rose from $7 trillion in 2000 to

$12 trillion in 2007 (Statista, 2020), while institutional investors' assets under management by independent asset managers rose from $79 trillion to $157 trillion (Gerakos et al., 2016). Following the financial crisis, net assets of mutual funds fell to $9.6 trillion and institutional investor assets under management fell to $36.8 trillion in 2008. Some financial commentators, including Rajan (2008), argued the increase in delegated investment management contributed to the crisis. They suggested investment managers invested in these mortgage-backed securities to increase their short-term returns to attract funds despite their exposure to tail risk.

This narrative about the role of delegated investment management in the 2007 financial crisis echoes the Hyman Minsky (1992) financial instability hypothesis. Minsky argued that long periods of stability are often accompanied by a build-up of risk that increase the size of subsequent crashes. While his ideas were often referenced by financial commentators as a possible explanation for the crash (e.g., Cassidy (2008)), Minsky's lack of a formal model makes it difficult to evaluate this hypothesis. Models formalizing the financial instability hypothesis (e.g., Bhattacharya et al. (2015)) focus on the role of learning about the distribution of asset returns and don't examine the role of delegated investment management.

In this paper, I show an economy with delegated investment management and assets with correlated tail risk will endogenously generate boom-bust cycles in output where longer periods of stability lead to larger crashes. In such an economy, assets under management grow during periods of stability and fall sharply after a crash. I examine a dynamic model where savers have limited access to investment technologies. On their own, they must invest their wealth in a risk-free asset. Some savers are matched with an investment manager. These matched savers can instead delegate their wealth to their investment manager, and investment managers can potentially generate higher average returns than the return of the risk-free asset. Savers cannot observe their manager's ability or portfolio choices. They can fire their manager after observing their returns each period, and unmatched savers may randomly match with a new manager.

Investment managers are born with high or low ability, and they exit the economy when fired or exogenously separated. Each period, they choose to invest the delegated wealth either in a risky project or a tail-risk project. Risky projects have a constant price, and their output depends on the investment manager's ability. The output of a tail-risk project is affected by the aggregate shock but is not affected by the manager's ability. Tail-risk projects generate high average output when the aggregate shock is good and generate no output when the aggregate shock is bad. The price of tail-risk projects is increasing with their quantity and is high enough such that their expected return is strictly lower than that of a risky project.

Despite the lower expected return of tail-risk projects, I show that a strictly positive fraction of low-ability managers will invest in tail-risk projects in equilibrium. The career concerns of low-ability managers are responsible for this preference. Savers use returns as a signal of manager ability and fire managers who they believe have low ability. For a low-ability manager, investing in a tail-risk project generates returns which are less likely to differ from the returns generated by a high-ability manager.

I parameterize the model to US data and conduct numerical exercises to examine the dynamic properties of this model. With the benchmark parameter values, all low-ability managers invest in tail-risk projects in equilibrium. If the tail-risk project did not exist, low-ability managers would invest in risky projects and they would be fired at a constant rate. The population of low-ability managers would converge to a steady-state value. When the tail-risk project exists, only a small fraction of low-ability managers are fired after a good aggregate shock since the higher returns of tail-risk projects makes it more difficult for savers to identify low-ability managers. The population of low-ability managers increases in these periods. After a bad aggregate shock, tail-risk projects produce no output and all low-ability managers are fired. With longer periods of consecutive good shocks, assets under management increase, more assets are invested in tail-risk projects, and the price of tail-risk projects is commensurately higher. The fall in output, assets under management, and the price of tail-risk projects are thus larger when a bad shock is preceded by longer booms.

This paper is closely related to studies on delegated investment management and assets with tail risk including Guerrieri and Kondor (2012), Makarov and Plantin (2015), and Malliaris and Yan (2015). These studies find low-ability managers prefer assets with left-skewed return distributions (i.e., assets with tail risk). Such assets allow low-ability managers to better mimic the returns of high-ability managers and thus reduce their chance of being fired. This preference generates a reputation premium in the price of assets with left-skewed return distributions. This paper contributes to this literature by showing this preference can generate boom-bust cycles where longer booms lead to larger crashes. In contrast with other models of boom-bust cycles, this model generates cycles even when the riskiness of the asset does not change and when investment managers are fully informed about the returns of the assets. Further, the boom-bust cycles generated by this mechanism exhibit increases in assets managed by investment managers during booms and reductions in assets under management following a crash, which is consistent with the data on assets under management.

More broadly, this paper is related to the literature on asset pricing and delegated investment management where the career concerns of investment managers cause assets to become mispriced. Scharfstein and Stein (1990) show if managers are judged both on their returns and whether they invested similarly to other managers, even informed managers may follow the investment behavior of other managers instead of trading based on the signals they receive. Assets are mispriced as not all available information on asset values are used. Allen and Gorton (1993) show investment managers will purchase assets at a price above their fundamental value if the managers have limited liability, where they do not lose money if the value of their investment falls. Goldman and Slezak (2003) show delegated investment management can create persistent mispricing in long-term assets if the return horizon of the asset is longer than the tenure of investment managers. Vayanos (2004) finds performance-based withdrawals induce investment managers to switch to safe assets when volatility is higher. These cause flights to quality and can exacerbate the volatility in asset prices.

Finally, this paper also contributes to the literature on generating boom-bust cycles where longer booms lead to larger crashes. Explanations for why long periods of stability lead to larger crashes usually feature learning, such as in Broer and Kero (2012), Boz and Mendoza (2014), and Bhattacharya et al. (2015). These studies consider models where agents must learn the transition probabilities between high- and low-volatility regimes. A prolonged period of one volatility regime leads agents to underestimate the true transition probability and expose themselves to greater losses when the volatility regime changes. This paper demonstrates an alternative mechanism that generates boom-bust cycles, which can also generate patterns in assets under management similar to those seen in the data.

Section 3.2 describes the model. The equilibrium is defined in Section 3.3. In Section 3.4, I conduct numerical exercises with the model. In Section 3.5, I consider the effects of varying the parameters. Section 3.6 concludes.

3.2 Model

The economy is populated by two types of agents: savers and investment managers, along with three types of assets: the risk-free asset, risky projects, and tail-risk projects. Time in this economy is discrete and infinite-horizon, and is indexed by $t = \{0, 1, ...\}$. Each period is divided into three sub-periods: morning, afternoon, and evening. In the morning, savers are endowed with wealth. They must choose whether to invest their wealth in a risk-free asset or delegate their wealth to their matched investment manager. Investment managers do not receive an endowment, but choose to invest assets delegated to them by the saver in a risky project or in a tail-risk project. In the afternoon, an aggregate shock which affects the output of tail-risk projects is realized, assets generate output, and agents consume their total wealth. The matching process occurs in the evening. New managers enter and are randomly matched with an unmatched saver. Some matches are exogenously terminated, and the remaining matched savers choose whether to fire or retain their manager.

3.2.1 Projects

Projects are one-period infinitely-divisible assets which only investment managers have the expertise to invest in. There are two types of projects, denoted by j: risky projects ($j = R$) and tail-risk projects ($j = T$). Investment managers invest in projects in the morning, and the projects generate output in the afternoon. The cost of producing projects are abstracted with price functions. Investing in one unit of a project of type j costs $c^j(A_t^j)$ units of wealth, where A_t^j is the total quantity of projects of type j in period t. The output of a project is denoted $y_{i,t}^j$.

The output of a risky project is $y_t^R \sim U[\rho_L, \bar{\rho}]$ with probability $1-\epsilon$ and $y_t^R = 0$ with probability ϵ, where $\epsilon \approx 0$. I consider the limit case of $\epsilon \to 0$ to simplify notation. Risky projects have a constant cost, normalized to $c_R(A_t^R) = 1$. As such, the return of investing in a risky project $r_{i,t}^R$ is equal to its output $y_{i,t}^R$.

In the morning, each potential risky project issues a signal $\theta \in \{\bar{\theta}, \underline{\theta}\}$ that only managers with high ability observe. The signal reveals whether the project's return will be greater than or less than ρ_H, where $\rho_L < \rho_H < \bar{\rho}$. The signal is good ($\theta = \bar{\theta}$) if $y^R \geq \rho_H$ and is bad ($\theta = \underline{\theta}$) otherwise. As such, a manager with high ability that decides to invest in a risky project will choose one with a good signal and will generate returns $r_{i,t}^R \sim U[\rho_H, \bar{\rho}]$. A manager with low ability that chooses to invest in a risky project must choose a random project and will generate returns $r_{i,t}^R \sim U[\rho_L, \bar{\rho}]$.

The output of tail-risk projects depend on the aggregate shock. Before returns are realized in the afternoon, an aggregate shock $s_t \in \{\bar{s}, \underline{s}\}$ is drawn where $\Pr[s_t = \underline{s}] = \phi$. When the good shock occurs ($s_t = \bar{s}$), tail-risk projects produce output $y_t^T \sim U[\rho_H, \bar{\rho}]$. When the bad shock occurs ($s_t = \underline{s}$), tail-risk projects do not produce any output ($y_t^T = 0$). I assume the probability of the bad shock is $\phi = \frac{\rho_H - \rho_L}{\rho_H + \bar{\rho}}$ to equalize the expected output of tail-risk projects with the expected output of risky projects.

Tail-risk projects are in limited supply, and the cost of each project increases with the quantity of tail-risk projects. I use an upward-sloping price function to abstract from a perfectly-competitive market where producers face an increasing marginal cost of supplying tail-risk projects for investment. The price of investing in one unit of tail-risk projects is $c^T(A_t^T) = 1 + \gamma A_t^T$, where the parameter $\gamma > 0$ is the slope parameter of the price function and A_t^T is the quantity of tail-risk projects demanded in period t. The return from investing 1 unit of wealth in a tail-risk project is thus $r_{i,t}^T = \frac{y_{i,t}^T}{c_t^T} = \frac{y_{i,t}^T}{1+\gamma A_t^T}$. By construction, the expected return of risky projects is greater than the expected return of tail-risk projects since their expected outputs are equal and the price of the tail-risk project is strictly greater than 1.[1]

3.2.2 Savers

There is a continuum of measure M of identical savers who are indexed by i. Savers are risk-neutral and their discount factor is β.

In the morning, savers are endowed with 1 unit of wealth and make their investment decision. Savers do not have the expertise to invest directly in projects. When they are not matched with an investment manager, they can only invest their endowment in the risk-free asset which generates 1 unit of output in the afternoon. Savers that are matched with an investment manager can instead delegate their endowment to the manager for investment in a project. If they do, they must pay the investment manager an exogenous fraction τ of returns as the management fee. In the absence of career concerns, this contract would fully align the incentives of the saver and the investment manager.

Savers have limited information about their matched manager and the projects. They can't observe their investment manager's portfolio choice. Savers also have limited information about the investment manager they are matched with. They are not able to directly observe their manager's ability. They know the fraction of new investment managers that have high and low ability and have accurate beliefs about the distribution of returns each type of manager generates when investing in the risky project. Finally, I assume savers are unaware of the existence of the tail-risk project.[2] Savers form beliefs about the probability their manager has high ability, denoted by $q_{i,t}$, based on the history of their manager's returns.

Savers consume their full returns and update their beliefs in the afternoon of each period. Savers not matched with an investment manager or who did not delegate their wealth to their investment manager consume their returns from saving, normalized to $r_{i,rf} = 1$. Savers who delegated their

[1] In this model, I assume manager ability does not affect the return of the tail-risk project. As discussed in Section 3.3.2, this assumption is not crucial for the results of the model. High-ability managers would not invest in tail-risk projects even if they had the same expected return as risky projects because doing so would increase the manager's chance of being fired.

[2] This assumption is required for the saver's firing decision to be stationary.

wealth to a manager consume the returns generated by their manager's investments net of fees $(1-\tau)r_{i,del}$. Matched savers enter each period t with the beliefs $q_{i,t-1}$. After observing the returns generated by their matched manager in period t, these beliefs are updated to $q_{i,t}$.

The matching process occurs in the evening. Each unmatched saver has an equal probability μ_t to be matched with a newly entering manager. For previously-matched savers, a fraction δ have their matches exogenously terminated. The remaining matched savers choose to fire or retain their manager. The saver's firing decision is denoted $f_{i,t} \in \{1, 0\}$, where $f_{i,t} = 1$ means the saver fires the manager and $f_{i,t} = 0$ means the saver retains the manager.

3.2.3 Investment Managers

Investment managers have the expertise to invest in projects but are not endowed with any wealth. Investment managers are born with an ability which is high ($\alpha = H$) with probability λ or low ($\alpha = L$) with probability $1 - \lambda$. The manager's ability affects their returns when investing in risky projects. They are matched one-to-one with a saver and are indexed by their matched saver i. Investment managers invest the wealth delegated to them by their matched saver in exchange for a management fee equal to a constant fraction τ of the returns they generate. As with savers, investment managers are risk-neutral and their discount factor is β.

In the morning, managers who are delegated wealth from their matched saver choose a project to invest in. Managers must invest in a single risky project or tail-risk project. Projects are infinitely-divisible, so 1 unit of delegated wealth funds $\frac{1}{c^j(A_t^j)}$ units of the project the manager chooses to invest in. The manager with ability α matched with saver i chooses a probability of investing in a tail-risk project $d_{i,t}^{\alpha} \in [0, 1]$, with a complementary probability of investing in a risky project. The measure of managers of type α which invests in a tail-risk project in period t is $D_t^{\alpha} = \int d_{i,t}^{\alpha}\, di$.

When choosing a project to invest in, high-ability managers observe the signal θ issued by risky projects. As such, when high-ability managers invest in a risky project, they can choose a project with $\theta = \bar{\theta}$ and thus generates returns $r_{i,t}^R \sim [\rho_H, \bar{\rho}]$. Low-ability managers do not observe this signal and generate returns $r^R_{i,t} \sim [\rho_L, \bar{\rho}]$ when they invest in a risky project. The return of managers of any ability that invest in a tail-risk project is $r^T_{i,t} \sim U[\frac{\rho_H}{c^T_t(A^T_t)}, \frac{\bar{\rho}}{c^T_t(A^T_t)}]$ if the aggregate shock was good ($s_t = \bar{s}$) and $r^T_{i,t} = 0$ if the aggregate shock was bad ($s_t = \underline{s}$). Investment managers receive and consume a fraction τ of the realized return in the afternoon, and the remainder is passed on to their matched saver.

Unlike savers, investment managers exit and enter the model. The measure of managers in the morning and afternoon of period t is denoted N^H_t for high-ability managers and N^L_t for low-ability managers. In the evening, a constant measure n new managers are born and are randomly matched with unmatched savers. Managers that are fired or exogenously terminated exit the economy, earning a continuation value of 0.

3.3 Equilibrium

In this section, I describe the problems of the saver, the high-ability manager, and the low-ability manager. I then define the symmetric recursive equilibrium for this economy, focusing on the case where savers want to delegate to high-ability investment managers and fire low-ability managers.

3.3.1 Saver's Problem

In the morning of each period, savers that are matched with an investment manager must choose to invest their endowment in the risk-free asset or delegate it to their manager. An unmatched saver must invest their wealth in the risk-free asset. In the afternoon, savers consume their returns and update their beliefs on their matched manager's ability. In the evening, matched savers choose whether to fire or retain their matched manager, and unmatched savers may randomly match with new managers.

The matched savers' firing decisions are based on their beliefs about the expected returns their managers would generate. Savers fire their manager if the perceived continuation value of being matched with their current manager is lower than the continuation value of being unmatched, where they save until they are matched with a new manager. The saver's continuation value of being matched with their current manager depends on the saver's beliefs on their manager's ability.

Because savers can't directly observe their matched manager's ability, they use the returns generated by their matched manager to update their beliefs $q_{i,t}$ on the probability their matched manager has high ability. After observing the returns $r_{i,t}$ generated by their matched manager, savers update their beliefs according to Bayes' Rule:

$$q_{i,t} = \tilde{q}_{i,t-1}\left(\frac{Pr(r_{i,t}|H)}{Pr(r_{i,t}|H)\tilde{q}_{i,t-1} + Pr(r_{i,t}|L)(1-\tilde{q}_{i,t-1})}\right)$$

$$\text{where } \tilde{q}_{i,t-1} = \begin{cases} q_{i,t-1} & \text{if matched with manager prior to morning of previous period;} \\ \lambda & \text{if matched with manager in evening of previous period.} \end{cases} \tag{3.1}$$

Since savers are unaware of the tail-risk project, they perceive the conditional probabilities as:

$$Pr(r_{i,t}|H) = \begin{cases} \frac{1}{\bar{\rho}-\rho_H} & \text{for } r_{i,t} \in [\rho_H, \bar{\rho}]; \\ 0 & \text{for } r_{i,t} < \rho_H. \end{cases} \tag{3.2}$$

$$Pr(r_{i,t}|L) = \begin{cases} \frac{1}{\bar{\rho}-\rho_L} & \text{for } r_{i,t} \in [\rho_L, \bar{\rho}]; \\ \epsilon & \text{for } r_{i,t} = 0. \end{cases} \tag{3.3}$$

When a saver observes their manager generating a return $r_{i,t} < \rho_H$, they believe their manager could not have generated those returns unless the manager had low ability. The saver's beliefs become $q_{i,t} = 0$ regardless of their previous beliefs on their manager's ability. When a saver observes a return $r_{i,t} \geq \rho_H$, they believe high-ability managers are more likely to generate those returns than low-ability managers, and $q_{i,t} \geq q_{i,t-1}$.

The saver's beliefs on their matched manager's ability determines their investment decisions in the morning and their firing decisions in the evening. In the morning, an unmatched saver must invest their endowment in the risk-free asset. A matched saver's decision on whether to save or delegate their wealth depends on their perceived expected return of delegating to their manager.

Since savers are unaware of the tail-risk project, the matched saver's value function in the morning $W_{i,t}(q_{i,t-1})$ is as follows:

$$W_{i,t}(q_{i,t-1}) = \max\{1\,,\,(1-\tau)E[r^R(q_{i,t-1})]\} \tag{3.4}$$

The first term is the return on the risk-free asset $r_{i,rf} = 1$. The second term is the after-fee expected return from delegating to an investment manager whose probability of having high ability is $q_{i,t-1}$.

To ensure savers want to delegate to high-ability investment managers and not to low-ability managers, I make the following assumptions on project returns:

$$(1-\tau)\frac{1}{2}(\rho_H + \bar{\rho}) > 1 \tag{3.5}$$

$$(1-\tau)\frac{1}{2}(\rho_L + \bar{\rho}) \leq 1 \tag{3.6}$$

$$(1-\tau)\frac{1}{2}[\lambda(\rho_H + \bar{\rho}) + (1-\lambda)(\rho_L + \bar{\rho})] \geq 1 \tag{3.7}$$

Equation 3.5 requires the after-fee expected return of a high-ability manager investing in a risky project to be greater than the return on the risk-free asset. Equation 3.6 requires the after-fee expected return of a low-ability manager investing in a risky project to be lower than or equal to the return on savings. These two assumptions imply savers want to delegate to high-ability managers and not to low-ability managers. Finally, Equation 3.7 requires the after-fee expected return of a random newly-matched manager to be greater than or equal to the return on savings. This guarantees savers are willing to delegate their wealth to a newly-matched manager.

These expected returns affect the matching process. Savers who were unmatched in the current period become matched with a newly-entering investment manager with probability μ_t. The value function for an unmatched saver going into the matching process $U_{i,t,u}$ averages the continuation value if they are matched with a new manager this period and the continuation value if they remain unmatched.

$$U_{i,t,u} = \mu_t \beta E[r^R_{i,t+1}(\lambda) + U_{i,t+1,m}(q_{i,t+1})] + (1 - \mu_{t+1})\beta[1 + U_{i,t+1,u}] \tag{3.8}$$

A measure n new investment managers enter each period and each unmatched saver has an equal chance to match with them. The probability of an unmatched saver matching with an entering manager is the measure of entering managers divided by the measure of unmatched savers:

$$\mu_t = \frac{n}{M - N^L_t - N^H_t} \tag{3.9}$$

For matched savers, a fraction δ have their matches exogenously terminated. These savers will enter the next period as an unmatched saver. The value function of savers who had their matches exogenously terminated is the continuation value of being unmatched in the next period:

$$U_{i,t,\delta} = \beta[1 + U_{i,t+1,u}] \tag{3.10}$$

Matched savers whose matches are not exogenously terminated must choose to fire or retain their manager. Their value function in the evening is the greater of the continuation values for firing their manager and for retaining their manager:

$$U_{i,t,m}(q_{i,t}) = \max_{f_{i,t} \in \{0,1\}} \{U(f_i, q_i)\} \tag{3.11}$$

$$U(0, q_{i,t}) = \beta E\left[W_{i,t+1}(q_{i,t}) + \delta U_{i,t+1,\delta} + (1 - \delta)U_{i,t+1,m}(q_{i,t+1})\right] \tag{3.12}$$

$$U(1, q_{i,t}) = \beta\left[1 + U_{i,t+1,u}\right] \tag{3.13}$$

The value function of savers that fire their manager is the continuation value of an unmatched saver. Savers who retain their manager receive a continuation value which depends on their beliefs on their manager's ability $q_{i,t}$. These beliefs determine their perceived expected return from delegating to their manager next period.

The equilibrium firing decisions can be characterized by examining how saver beliefs evolve. As discussed with Equations 3.2 and 3.3, a saver's belief $q_{i,t}$ increases and is greater than λ when their manager generates returns $r_{i,t} \geq \rho_H$, and falls to zero when $r_{i,t} < \rho_H$. With the assumptions on project returns (Equations 3.5 - 3.7), savers will never retain their manager while intending to invest in the risk-free asset next period. Savers would only invest in the risk-free asset instead of delegating their wealth to their matched manager if they believe their matched manager is less likely to have high ability than a random new manager. In that case, firing their matched manager and having the chance to match with a random new manager next period strictly dominates retaining their matched manager.

As such, the matched savers' firing decisions $f_{i,t}$ depend only on the current period's returns:

$$f_{i,t}(r_{i,t}) = \begin{cases} 0 & \text{if } r_{i,t} \in [\rho_H, \bar{\rho}]; \\ 1 & \text{if } r_{i,t} < \rho_H. \end{cases} \tag{3.14}$$

Savers whose managers produced returns $r_{i,t} \geq \rho_H$ this period will retain their manager. These savers have $q_{i,t} \geq \lambda$, which implies $(1-\tau)r^R(q_{i,t}) \geq 1$ (Equation 3.7). These savers would retain their managers as $U(0, q_{i,t}) \geq U(1, q_{i,t})$. Savers with managers who produced a return $r_{i,t} < \rho_H$ believe their manager has low ability. The after-fee return from delegating to a low-ability manager is less than the return from the risk-free asset (Equation 3.6), so savers would not want to delegate to a low-ability manager in future periods. As such, savers will fire their manager if the manager generates a return $r_{i,t} < \rho_H$.

Because the firing decisions depend only on the current period return and not the saver's prior beliefs, the distribution of saver beliefs does not need to be tracked. Additionally, the probability of matching with a new manager μ_t does not need to be tracked since it does not affect the saver's equilibrium firing decisions. Managers are only endogenously fired when they are revealed to have low ability with certainty, so these firing decisions are optimal for any chance of matching with a manager.

3.3.2 Investment Manager's Problem

From the results of the saver's problem, all investment managers will be delegated one unit of wealth by their matched saver in the morning of each period. The manager matched with saver i with ability α must choose a probability of investing in a tail-risk project $d^{\alpha}_{i,t}$, with a complementary probability $1 - d^{\alpha}_{i,t}$ of investing in a risky project. Investment managers take the price of tail-risk projects c^{T}_{t} as given. The value function of a manager in the morning is:

$$V^{\alpha}_{i,t} = \max_{d^{\alpha}_{i,t} \in [0,1]} \left\{ (1 - d^{\alpha}_{i,t}) V^{\alpha,R}_{i,t} + d^{\alpha}_{i,t} V^{\alpha,T}_{i,t} \right\} \tag{3.15}$$

where $V^{\alpha,R}_{i,t}$ is the value of investing the unit of delegated wealth in a risky project and $V^{\alpha,T}_{i,t}$ is the value of investing in a tail-risk project:

$$\begin{aligned} V^{\alpha,R}_{i,t} =& \tau E[r^{R}_{i,t}(\alpha)] + (1 - \phi)\beta(1 - \delta)Pr[f_{i,t} = 0|R, \alpha] \; V^{\alpha}_{i,t+1}(\bar{s}) + \\ & + \phi\beta(1 - \delta)Pr[f_{i,t} = 0|R, \alpha] \; V^{\alpha}_{i,t+1}(\underline{s}) \end{aligned} \tag{3.16}$$

$$\begin{aligned} V^{\alpha,T}_{i,t} =& \tau E[r^{T}_{i,t}(c^{T}_{t})] + (1 - \phi)\beta(1 - \delta)Pr[f_{i,t} = 0|T, \bar{s}] \; V^{\alpha}_{t+1}(\bar{s}) + \\ & + \phi\beta(1 - \delta)Pr[f_{i,t} = 0|T, \underline{s}] \; V^{\alpha}_{i,t+1}(\underline{s}) \end{aligned} \tag{3.17}$$

The first term in Equations 3.16 and 3.17 is the expected fee earned during the current period. The second term is the continuation value with a good shock ($s = \bar{s}$), and the last term is the continuation value with a bad shock ($s = \underline{s}$).

The investment manager's value functions depend on their ability because high-ability managers and low-ability managers generate different returns when investing in a risky project. This affects their current-period returns and their probability of being fired. In the following two subsections, the high-ability manager's problem and the low-ability manager's problem are examined separately.

High-Ability Manager's Problem

High-ability managers observe the signal θ on risky projects and can screen out risky projects that will generate returns below ρ_H. As such, the return generated by a high-ability manager investing in a risky project produces returns $r_{i,t} \sim U[\rho_H, \bar{\rho}]$, and high-ability managers are never endogenously fired when they invest in risky projects (see Section 3.3.1). The value function for a high-ability manager investing in a risky project is:

$$V_{i,t}^{H,R} = \tau \frac{1}{2}(\rho_H + \bar{\rho}) + (1-\phi)\beta(1-\delta)V_{i,t+1}^{H}(\bar{s}) + \phi\beta(1-\delta)V_{i,t+1}^{H}(\underline{s}) \tag{3.18}$$

A high-ability manager who invests in a tail-risk project generates a return $r_{i,t} \sim U[\frac{\rho_H}{c_t^T}, \frac{\bar{\rho}}{c_t^T}]$ when the aggregate shock is good with probability $1-\phi$ and $r_{i,t} = 0$ when the aggregate shock is bad with probability ϕ. Because savers fire managers who generate returns less than ρ_H in equilibrium, there are two ways high-ability managers can be fired when investing in a tail-risk project. First, if the aggregate shock is bad, the manager generates 0 returns and will be fired. Second, even when the aggregate shock is good, the manager will be fired if they generate a return $\frac{\rho_H}{c_t^T} \leq r_{i,t} < \rho_H$. As such, the value function for a high-ability manager investing in a tail-risk project is:

$$V_{i,t}^{H,T} = \tau \frac{1}{2}(1-\phi)\frac{\rho_H + \bar{\rho}}{c_t^T} + (1-\phi)\beta(1-\delta)\left(\frac{\frac{\bar{\rho}}{c_t^T} - \rho_H}{\frac{\bar{\rho}-\rho_H}{c_t^T}}\right)V_{i,t+1}^{H}(\bar{s}) \tag{3.19}$$

For high-ability managers, investing in a tail-risk project results in lower expected fees earned in the current period and a higher probability of being fired.[3] As a result, $V_{i,t}^{H,R} > V_{i,t}^{H,T}$ and high-ability managers always choose to invest in a risky project:

$$d_{i,t}^{H} = D^{H} = 0 \tag{3.20}$$

The high-ability manager's value function is thus the expected value of investing in a risky project

[3]Even if high-ability managers generated the same expected returns when investing in a tail-risk project as when they invest in a risky project, the exposure to the aggregate shock means they will face a strictly positive chance to be fired when they invest in the tail-risk project. As such, high-ability managers would still invest in a risky project.

each period until the match is exogenously terminated:

$$V_{i,t}^{H} = V^{H} = \tau \frac{1}{1-\beta(1-\delta)} \frac{1}{2}(\rho_H + \bar{\rho}) \tag{3.21}$$

Low-Ability Manager's Problem

Low-ability managers do not observe the signal θ on risky projects, so they cannot screen out risky projects that will generate returns below ρ_H. The return generated by a low-ability manager investing in a risky project is $r_{i,t} \sim U[\rho_L, \bar{\rho}]$. Unlike high-ability managers, a low-ability manager investing in a risky project will generate returns low enough to be fired by savers with probability $\frac{\rho_H - \rho_L}{\bar{\rho} - \rho_L}$. Their value function when investing in a risky project is:

$$\begin{aligned} V_{i,t}^{L,R}(N_t^L, c_t^T) = \tau\frac{1}{2}(\rho_L + \bar{\rho}) + (1-\phi)\beta(1-\delta)\left(\frac{\bar{\rho}-\rho_H}{\bar{\rho}-\rho_L}\right) V_{i,t+1}^{L}\left(N_{t+1}^{L}(N_t^L, \bar{s}), c_{t+1}^{T}\right) + \\ + \phi\beta(1-\delta)\left(\frac{\bar{\rho}-\rho_H}{\bar{\rho}-\rho_L}\right) V_{i,t+1}^{L}\left(N_{t+1}^{L}(N_t^L, \underline{s}), c_{t+1}^{T}\right) \end{aligned} \tag{3.22}$$

Because manager ability does not affect the returns of tail-risk projects, the value function for a low-ability manager investing in a tail-risk project is similar to that of the high-ability manager's value function described in Section 3.3.2, with the exception that the continuation value is that of a low-ability manager.

$$V_{i,t}^{L,T}(N_t^L, c_t^T) = \tau\frac{1}{2}(1-\phi)\frac{\rho_H + \bar{\rho}}{c_t^T} + (1-\phi)\beta(1-\delta)\left(\frac{\frac{\bar{\rho}}{c_t^T} - \rho_H}{\frac{\bar{\rho}-\rho_H}{c_t^T}}\right) V_{i,t+1}^{L}\left(N_{t+1}^{L}(N_t^L, \bar{s}), c_{t+1}^{T}\right) \tag{3.23}$$

The low-ability manager's investment decision, the probability of investing in a tail-risk project $d_t^L(N_t^L)$, depends on the difference between these two value functions. For a low-ability manager, the difference in expected value between investing in a tail-risk project and investing in a risky project can be written as $\Delta V_{i,t}^{L}(N_t^L, c_t^T) = V_{i,t}^{L,T}(N_t^L, c_t^T) - V_{i,t}^{L,R}(N_t^L, c_t^T)$:

$$\Delta V_{i,t}^{L}(N_t^L,\ c_t^T) = \Delta CurrentVal + \Delta ContBad + \Delta ContGood \tag{3.24}$$

$$\Delta CurrentVal = -\left(1 - \frac{1}{c_t^T}\right)\tau\frac{1}{2}(\rho_L + \bar{\rho}) \tag{3.25}$$

$$\Delta ContBad = -\beta(1-\delta)\left(\frac{\bar{\rho} - \rho_H}{\bar{\rho} - \rho_L}\right)\phi\, V_{i,t+1}^{L}\left(N_{t+1}^{L}(N_t^L, \underline{s}), c_{t+1}^T\right) \tag{3.26}$$

$$\Delta ContGood = \beta(1-\delta)\left(\frac{\bar{\rho} - (c_t^T)\rho_H}{\bar{\rho} - \rho_H} - \frac{\bar{\rho} - \rho_H}{\bar{\rho} - \rho_L}\right)(1-\phi)V_{i,t+1}^{L}\left(N_{t+1}^{L}(N_t^L, \bar{s}), c_{t+1}^T\right) \tag{3.27}$$

A low-ability manager strictly prefers to invest in a tail-risk project if $\Delta V_{i,t}^L$ is positive, strictly prefers to invest in a risky project if $\Delta V_{i,t}^L$ is negative, and is indifferent between investing in a tail-risk project and investing in a risky project if $\Delta V_{i,t}^L = 0$. The $\Delta CurrentVal$ term reflects the loss in current-period expected fees earned. This term is negative because the expected return of a tail-risk project is less than that of a risky project. The $\Delta ContBad$ term is the expected loss in continuation value if the aggregate shock is bad. This term is also negative since managers investing in tail-risk projects are fired with certainty after a bad shock. The $\Delta ContGood$ term reflects the expected gain in continuation value if the aggregate shock is good, which reflects a lower chance of being fired. In equilibrium, this term must be positive. Low-ability managers would stop investing in tail-risk projects before the price of tail-risk projects c_t^T was high enough such that tail-risk projects have a lower chance of generating returns greater than ρ_H. This shows the low-ability managers' career concerns are the only reason they would invest in tail-risk projects.

The value of $\Delta V_{i,t}^L$ and whether low-ability managers prefer to invest in a risky project or a tail-risk project depends on the price of tail-risk projects c_t^T. If c_t^T is low, the difference in the current-period expected fees earned would be small and the probability of being endogenously fired after a good shock would be much lower when investing in a tail-risk project. In this case, the value of investing in a tail-risk project would be higher than the value of investing in a risky project ($\Delta V_{i,t}^L > 0$), and low-ability managers would strictly prefer to invest in a tail-risk project. Investing in a risky projects becomes relatively more attractive as c_t^T increases. If c_t^T was sufficiently large such that $\Delta V^L_{i,t} < 0$, low-ability managers would strictly prefer to invest in a risky project. In equilibrium, c^T_t would never attain a level such that $\Delta V^L_{i,t} < 0$. Instead, low-ability managers would play a mixed strategy between investing in a risky project and investing in a tail-risk project, and the equilibrium c^T_t would be such that low-ability managers are indifferent between investing in the two types of projects ($\Delta V^L_{i,t} = 0$).

Because the continuation values depend on future prices and populations of low-ability managers, the low-ability manager's problem does not have an analytical solution like the high-ability manager's problem. In Section 3.4, the low-ability manager's policy function for the probability of investing in a tail-risk project $d^L_{i,t}(N^L_t)$ will be computed numerically.

3.3.3 Evolution of Manager Populations, Symmetry, and Market Clearing

Three additional sets of conditions are required to close the model. The first set describes the evolution of manager populations. Manager populations decrease with exogenous separations and the savers' endogenous firing decisions, and they increase with new entering managers. The population of high-ability managers N^H_t and low-ability managers N^L_t evolve according to the following equations:

$$N^H_{t+1} = (1-\delta)(1-F^H_t)N^H_t + \lambda n \tag{3.28}$$

$$N^L_{t+1} = (1-\delta)(1-F^L_t)N^L_t + (1-\lambda)n \tag{3.29}$$

where F^α_t is the fraction of managers with ability α who are fired by their saver:

$$F^\alpha_t = \frac{1}{N^\alpha_t}\int_{\alpha_i=\alpha} f_{i,t}\, di \tag{3.30}$$

In equilibrium, savers do not endogenously fire high-ability managers and $F^H_t = 0$, as discussed in Section 3.3.2. Because the exit rate of high-ability managers does not depend on the aggregate shock or any other time-varying parameters, N_t^H has a steady state value:

$$N_{ss}^H = \frac{\lambda n}{\delta} \tag{3.31}$$

The population of high-ability managers will converge to this steady-state value over time. For the symmetric recursive equilibrium, the population of high-ability managers is initialized at and remains at this steady-state level.

The exit rate of low-ability managers depends on their investment decisions, as can be seen from the saver's equilibrium firing decisions described in Equation 3.14. If low-ability managers only invested in risky projects, there would be a steady-state population of low-ability managers:

$$N_{ss}^L = \frac{(1-\lambda)n}{1-(1-\delta)\frac{\bar{\rho}-\rho_H}{\bar{\rho}-\rho_L}} \tag{3.32}$$

If some or all low-ability managers invest in tail-risk projects, then the exit rate of low-ability managers would depend on the aggregate shock and the equilibrium population of low-ability managers would fluctuate over time. When the aggregate shock is good ($s = \bar{s}$), only the managers investing in a tail-risk project or risky project that produce returns less than ρ_H will be fired, and those investing in the tail-risk project will be fired at a lower rate than those investing in a risky project. When the aggregate shock is bad ($s = \underline{s}$), all managers investing in tail-risk projects are fired while those who invested in a risky project are fired at the normal rate. As such, the equilibrium population of low-ability managers evolves according to the following equations:

$$N_{t+1}^L(N_t^L, D_t^L, \bar{s}) = (1-\delta)\left[\frac{\bar{\rho}-(c_t^T)p_H}{\bar{\rho}-\rho_H}D_t^L + \frac{\bar{\rho}-\rho_H}{\bar{\rho}-\rho_L}(1-D_t^L)\right]N_t^L + (1-\lambda)n \tag{3.33}$$

$$N_{t+1}^L(N_t^L, D_t^L, \underline{s}) = (1-\delta)\left[\frac{\bar{\rho}-\rho_H}{\bar{\rho}-\rho_L}(1-D_t^L)\right]N_t^L + (1-\lambda)n \tag{3.34}$$

The second condition required to close the model addresses the relationship between individual manager decisions $d_{i,t}^\alpha$ and aggregate manager decisions D_t^α. The price of tail-risk projects c_t^T depends on the aggregate fraction of low-ability managers investing in tail-risk projects D_t^α. This introduces multiple equilibria into the model since different distributions of individual manager decisions can add up to the same fraction of managers investing in the tail-risk project.

To eliminate this multiplicity of equilibria, I consider only the symmetric equilibrium where all managers with the same ability must choose the same probability of investing in a tail-risk project:

$$d_{i,t}^{\alpha} = D_t^{\alpha}, \quad \forall \alpha \in \{H, L\} \tag{3.35}$$

Finally, a set of market clearing conditions for the tail-risk project is required. As discussed in Section 3.2.1, the market for tail-risk projects is abstracted using an upward-sloping price function c_t^T:

$$c_t^T(A_t^T) = 1 + \gamma A_t^T \tag{3.36}$$

where the total quantity of tail-risk projects A_t^T is defined as:

$$A_t^T = N_t^L D_t^L \tag{3.37}$$

3.3.4 Symmetric Recursive Equilibrium

A symmetric recursive equilibrium is the savers' belief functions $q'(q, r)$, perceived value functions $\left(W(q), U_m(q),\ U_u(q)\right)$, and policy functions $f(q)$; managers' value functions $\left(V^H, V^L(N^L, c^T)\right)$ and policy functions $\left(d^H, D^H, d^L(N^L, c^T), D^L(N^L)\right)$; the law of motion for manager populations $\left(N^H,\ N_{\bar{s}}'^L(N^L, D^L),\ N_{\underline{s}}'^L(N^L, D^L)\right)$; and prices $c^T(N^L, D^L)$:

1. *Given savers' beliefs on their matched manager's ability, the savers' value functions $\left(W_{i,t,m}(q_{i,t-1}) = W(q),\ U_{i,t,m}(q_{i,t}) = U_m(q),\ U_{i,t,\delta} = U_\delta,\ U_{i,t,u} = U_{unmatched}\right)$ and policy functions $\left(f_{i,t}(q_{i,t}) = f(q)\right)$ solve the saver's problem (eqs. 3.4, 3.8, 3.10, 3.11 - 3.13, 3.14);*

2. *The savers' beliefs $\left(q_{i,t+1}(q_{i,t}, r_{i,t}) = q'(q, r)\right)$ are consistent with Bayes' Law given savers' beliefs on manager decisions (eqs. 3.1, 3.2, 3.3);*

3. *The managers' value functions $\left(V_{i,t}^H = V^H,\ V_{i,t}^L(N_t^L, c_t^T) = V^L(N^L, c^T)\right)$ and policy functions*

$\left(d_{i,t}^H = d^H,\ d_{i,t}^L(N_t^L, c_t^T) = d^L(N^L, c^T)\right)$ are optimal given the savers' beliefs on manager decisions (eqs. 3.20, 3.21, 3.22, 3.23);

4. *Manager populations $\left(N_{t+1}^L(N_t^L, D_t^L, \bar{s}) = N_{\bar{s}}'^L(N^L, D^L),\ N_{t+1}^L(N_t^L, D_t^L, \underline{s}) = N_{\underline{s}}'^L(N^L, D^L),\ N^H\right)$ evolve according to manager and saver decisions and the history of shocks (eqs. 3.31, 3.33 - 3.34);*

5. *The individual manager's decisions are consistent with aggregate manager decisions such that $\left(d^H = D^H,\ d^L(N^L, c^T) = D^L(N^L, c^T)\right)$ (eq. 3.35);*

6. *The price of tail-risk projects $c_t^T(N_t^L, D_t^L) = c^T(N^L, D^L)$ clears the market for tail-risk projects (eq. 3.36, 3.37).*

I restrict attention to equilibria where $V^L(N^L, c^T)$ are weakly decreasing in N^L. I prove below that this restriction ensures $c^T(N^L)$ is single-valued and thus does not need to be tracked as a state variable. Further, it ensures that any equilibrium is unique.

Lemma 3.3.1. *If $V^L(N^L, c^T)$ is weakly decreasing in N^L, then $\Delta V^L(N^L) = V^{L,T}(N^L) - V^{L,R}(N^L)$ is strictly decreasing with D^L.*

Proof. Each component of $\Delta V^L(N^L)$ (see Equations 3.24 - 3.27) weakly decreases with D^L, and the difference in current-period returns strictly decreases with D^L. For the difference in current-period returns, Equation 3.25 shows that when D^L increases, the difference in current returns from investing in a tail-risk project compared to a risky project becomes more negative because the price of tail-risk projects increases.

For the difference in continuation values after a bad shock (Equation 3.26), an increase in D^L increases the number of low-ability managers fired and lowers the population of low-ability managers after the bad shock. From the assumption that $V^L(N^L, c^T)$ is weakly decreasing in N^L, the value of surviving after a bad shock $V'^L(N^L, \underline{s})$ increases or stays the same, so the difference in continuation values becomes more negative or remains equal.

For the difference in continuation values after a good shock (Equation 3.27), an increase in D^L increases the number of low-ability managers surviving and the population of low-ability managers. From the assumption that $V^L(N^L, c^T)$ is weakly decreasing in N^L, the value of surviving after a good shock $V'^L(N^L, \bar{s})$ decreases or stays the same, so the difference in continuation values after a good shock remains equal or becomes less positive. □

Theorem 3.3.2. *If $V^L(N^L, c^T)$ is weakly decreasing in N^L, then any equilibrium $D^L(N^L)$ and $c^T(N^L)$ are single-valued functions and unique.*

Proof. By contradiction. Assume $D^\star(N^L)$ and $c^\star(N^L)$ are one set of equilibrium functions, and $\hat{D}(N^L)$ and $\hat{c}(N^L)$ are a different set of equilibrium functions. Consider a value of $N^L = \bar{N}$ where (without loss of generality) $D^\star(\bar{N}) < \hat{D}(\bar{N})$, which implies $c^\star(\bar{N}) < \hat{c}(\bar{N})$ from Equations 3.36 - 3.37.

As discussed in Section 3.3.2, ΔV^L is strictly decreasing with c^T. From Lemma 3.3.1, ΔV^L is strictly decreasing with D^L. As such, $\Delta V^L(N^L, c^\star(\bar{N})) > \Delta V^L(N^L, \hat{c}(\bar{N}))$.

As discussed in Section 3.3.2, low-ability managers choose $d^L = 1$ when $\Delta V^L > 0$, $d^L = 0$ when $\Delta V^L < 0$, and $d^L \in [0, 1]$ when $\Delta V^L = 0$. If $\Delta V^L(N^L, c^\star(\bar{N})) > \Delta V^L(N^L, \hat{c}(\bar{N}))$, then $D^\star(\bar{N}) > \hat{D}(\bar{N})$, which is a contradiction. □

Corollary 3.3.3 (Theorem 3.3.2)**.** *Restricting attention to $V^L(N^L, c^T)$ which are weakly decreasing in N^L, any equilibrium $V^L(N^L)$ is unique.*

Proof. As per Equations 3.22 and 3.23, the low-ability manager's value function $V^L(N^L, c^T)$ depends only on N^L and c^T as state variables through the current-period expected consumption and the evolution of manager populations. By examination, the current-period expected consumption (first term in Equation 3.23) and the evolution of manager populations (Equations 3.33 and 3.34) are single-valued functions of c^T and N^L. By Theorem 3.3.2, the equilibrium $c^T(N^L)$ is single-valued and unique. As such, if an equilibrium $V^L(N^L, c^T)$ which is decreasing in N^L exists, it is unique. □

3.4 Results

In this section, I parameterize the model using US economic and asset management data. With these benchmark parameters, I compute the equilibrium low-ability manager's probability of investing in a tail-risk project. In equilibrium, low-ability managers only invest in tail-risk projects. There is a population above which low-ability managers would begin to play a mixed strategy, but that level is never attained in equilibrium.

The low-ability manager's probability of investing in a tail-risk project is used to simulate the economy with different patterns of shocks. The results show the combination of delegated investment management with career concerns and assets with correlated tail risk endogenously generate boom-bust cycles similar to those described by Minsky (1992). During a boom, the number of low-ability managers increases along with the quantity and price of the tail-risk project. The losses that would be experienced after a bad shock increase with the periods of consecutive good shocks preceding it.

3.4.1 Value Function Iteration

The equilibrium low-ability manager's value function $V^L(N^L)$ and probability of investing in a tail-risk project $D^L(N^L)$ are computed using value function iteration. The population of low-ability managers N^L is divided into a grid with 5000 values from $N^L = 0$ to $N^L = (1 - \lambda)M$, its maximum value if low-ability managers were never endogenously fired.[4] The initial guess is $D^L_0(N^L) = 0$ (here, the subscript 0 indicates the initial iteration), where all low-ability managers invest in risky projects. Investing only in risky projects is associated with the lower bound of the value function since this strategy is always available. The guessed $d^L(N^L)$ is used to generate a set of initial value functions $V^L_0(N^L)$.

For iteration ω, the previous iteration's value function $V^L_{\omega-1}(N^L)$ is used for the continuation

[4]Because low-ability managers are endogenously fired in equilibrium, the population of low-ability managers will not reach this maximum value unless it was initialized at that level. For completeness, I solve for the value and policy functions of low-ability managers across the full support of the population of low-ability managers.

value. The current iteration of the probability of investing in a tail-risk project $d^L_\omega(N^L) = D^L_\omega(N^L)$ is solved for using a bisection algorithm. For each value of N^L, the aggregate manager's probability of investing in a tail-risk project $D^L(N^L)$ is guessed and used to generate the price of the tail-risk project $c^T_\omega(N^L)$ and the next-period low-ability manager populations $N'^L_{\bar{s}}(N^L), N'^L_{\underline{s}}(N^L)$. The current iteration of manager decisions $d^L_\omega(N^L) = D^L_\omega(N^L)$ is found when the optimal individual low-ability manager's probability of investing in a tail-risk project $d^L(N^L)$ given these prices and continuation values is consistent with the aggregate probability $D^L(N^L)$.

If value function iteration produces a value function $V^L(N^L)$ and policy function $D^L(N^L)$ that converge, then an equilibrium exists and the low-ability manager's equilibrium value and policy functions have been found. A policy function $D^L(N^L)$ that converges implies that given the aggregate low-ability manager decisions $D^L(N^L)$, individual low-ability managers choose the policy function $d^L(N^L) = D^L(N^L)$. The equilibrium policy function can be used to solve for the equilibrium prices $c^T(N^L)$ and the law of motion of the population of low-ability managers $N'^L(N^L, \bar{s})$ and $N'^L(N^L, \underline{s})$, which satisfies the remaining conditions of the symmetric recursive equilibrium described in Section 3.3 that did not have analytic solutions.

3.4.2 Benchmark Parameters

I first conduct the numerical exercises using a benchmark set of parameter values specified in Table 3.1. While the model examined in this paper is stylized, I choose a set of parameter values based on U.S. economic and financial data. Each period of this model is assumed to be one year, with agents having an annual discount factor of 0.95. The population of savers M is normalized to 1 so manager populations and output are readily interpreted as per-saver values.

The manager's fixed fee is set as a fixed $\tau = 1.5\%$ of returns following the average manager's fee used by Berk and Green (2004). As long as Equation 3.7 holds such that the saver's perceived expected return of delegating to a new investment manager is greater than the return from savings, the choice of τ has no effect on the equilibrium outcomes. With the benchmark parameter values, τ must be less than 6% to satisfy this requirement.

Table 3.1: Benchmark parameter values

Parameter		Value
β	discount factor	0.95
τ	manager fee	0.015
M	measure of savers	1
λ	fraction of new managers with high ability	0.25
δ	exogenous separation rate	0.06
$\bar{\rho}$	max return of risky project	1.5
ρ_H	min return of risky project for high-ability managers	1.017
ρ_L	min return of risky project for low-ability managers	0.5
ϕ	probability of bad shock (derived)	0.167
n	measure of managers born each period	0.0525
γ	increase in tail-risk project's price with quantity	0.572

The probability of the bad shock is chosen to match the NBER average length of economic expansions from 1945 to 2009 of 58.4 months or 4.87 years. The parameter values on returns $\bar{\rho} = 1.5$ and $\rho_L = 0.5$ are chosen to set the return for a low-ability manager to 1. The parameter ρ_H, which represents both the minimum output of risky projects for high-ability managers and the minimum output of tail-risk projects, is set to 1.017 equate the expected output of tail-risk projects with that of risky projects for low-ability managers. These parameters imply an average return of 1.26 for high-ability managers investing in a risky project. While an average excess return for high-ability managers of 26% in this model is large compared to the data, a large excess return for high-ability managers is needed to generate a significant chance of low-ability managers being endogenously fired due to the use of uniform return distributions in this model.

As discussed in Section 3.3.1, savers infer their manager has low ability and thus fire managers if they generate returns below ρ_H. With the benchmark parameters, low-ability managers investing in a risky project have a 52% chance of being endogenously fired, which is much higher than the 21% chance of being fired if they invest in a tail-risk project when its price is close to 1. The price of the tail-risk project must be 1.19 before a low-ability manager investing in a tail-risk project faces the same chance of being fired, which corresponds with a quantity of assets invested in tail-risk projects of 0.93.[5]

[5] A higher price also reduces the expected current-period fees earned, so low-ability managers would strictly prefer

The parameters for the fraction of new managers with high ability λ is chosen to match stylized facts on mutual fund returns. Berk and Green (2004) estimate the average new manager of a mutual fund generates annual excess returns of 6.5% before fees. Since high-ability managers generate 26% higher returns when investing in a risky project, a fraction $\lambda = 0.25$ of new managers having high ability is needed for the average new manager to produce excess returns of 6.5% before fees.

The exogenous separation rate δ is chosen to match the steady-state ratio of high-ability to low-ability managers when there is no tail-risk project to the fraction of mutual funds with non-negative average excess returns. Barras et al. (2010) finds 75% of actively-managed U.S. mutual funds generated zero excess returns after fees on average, and 24% of funds generated negative average excess returns.[6] High-ability managers in this model are interpreted as the zero excess return managers and the low-ability managers are interpreted as the negative excess return managers. An exogenous separation rate of $\delta = 0.06$ generates a steady-state high-ability manager population of 0.83 and low-ability manager population of 0.27, which matches the 3-to-1 ratio seen in the data.

The population of entering managers each period n is parameterized based on the fraction of assets managed by investment managers. Gerakos et al. (2016) find 29% of institutional assets are managed by asset managers. I set $n = 0.0525$ such that the steady-state population of investment managers when there is no tail-risk project is 29% of the population of savers.

Finally, the slope parameter on the price of the tail-risk project γ must be parameterized. Based on the largest drop in the ABX index in 2008, Bhattacharya et al. (2015) use an expected return of mortgage-backed securities in the high-risk state at 0.92 in their study. For this model, a price of 1.09 for the tail-risk project corresponds with an expected return of 0.92. I set $\gamma = 0.572$ such that, if only good shocks were realized, the maximum population of low-ability managers sustained by a price of the tail-risk project of 1.09 generates the demand for tail-risk projects which is consistent with that price.

risky projects before the price of the tail-risk project reaches this level.

[6] Only a statistically insignificant percent of funds generated positive excess returns after fees.

3.4.3 Results of Numerical Exercises with Benchmark Parameters

I compute the equilibrium using the value function algorithm described in Section 3.4.1. Of interest are how the low-ability manager's probability of investing in a tail-risk project $d^L(N^L)$ and the price of the tail-risk project $c^T(N^L)$ change with the population of low-ability managers N^L. I use these results to simulate the economy with different patterns of shocks and show it experiences boom-bust cycles where longer booms are followed by larger crashes.

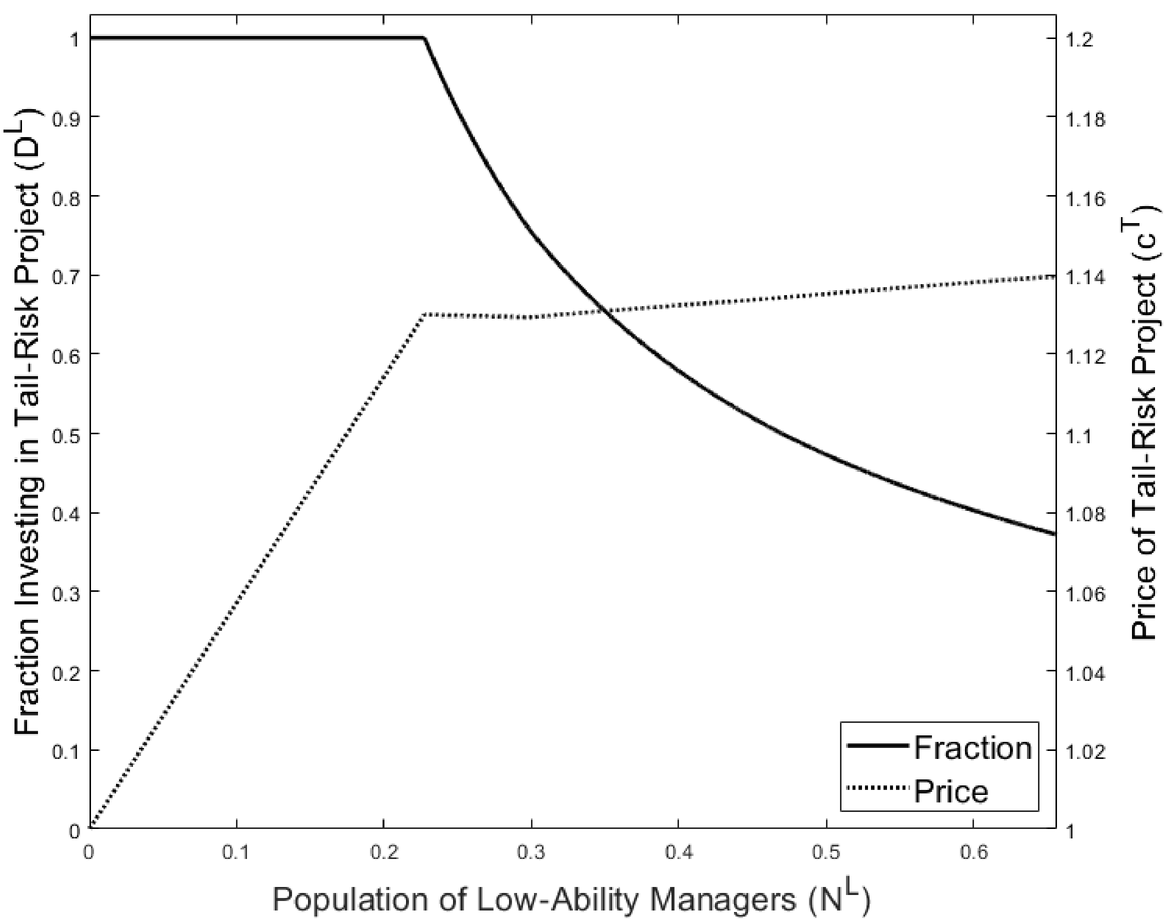
For the benchmark parameter values, the equilibrium low-ability manager's policy function and price of the tail-risk project are shown in Figure 3.1. As discussed in Section 3.3.2, the equilibrium fraction of low-ability managers investing in a tail-risk project is decreasing with N^L. Low-ability managers strictly prefer investing in a tail-risk project while N^L is less than 0.2272. The price of the tail-risk project c^T rises proportionally with N^L over this range.

When the population of low-ability managers N^L rises above 0.2272, low-ability managers become indifferent between investing in a tail-risk project and in a risky project, and the fraction of low-ability managers investing in a tail-risk project D^L strictly decreases with N^L in this region. The decrease in the fraction of low-ability managers investing in a tail-risk project is initially fast enough that the total assets invested in tail-risk projects slightly decreases with N^L from a quantity of 0.2272 to a minimum of 0.2261 at $N^L = 0.2993$. The price of the tail-risk project declines commensurately in this region.[7] Past that value, the price and quantity of the tail-risk project again increase with N^L.

While the policy function for the probability of investing in tail-risk projects exists for the full range of low-ability manager populations N^L, not all values of N^L are attainable in equilibrium. When the price of the tail-risk project rises, the return distribution of tail-risk projects shifts left and the probability that low-ability managers are fired increases. The simulations conducted below shows that the population of low-ability managers will converge to 0.1618 in this economy if the bad shock were never realized. This is below the threshold of $N^L = 0.2272$ where low-ability managers first begin to mix between the risky and tail-risk projects. In equilibrium, all low-ability

[7] In Figure 3.1, this is the region where the curve of the price of the tail-risk project flattens.

Figure 3.1: Fraction of low-ability managers investing in tail-risk project and derived equilibrium price of tail-risk project



Notes: This figure shows the equilibrium fraction of low-ability managers investing in a tail-risk project and the price of the tail-risk project derived from the manager decisions. These functions are computed using the benchmark parameter values in Table 3.1. The solid line is the policy function: the individual low-ability's probability of investing in a tail-risk project and the fraction of low-ability managers that invest in a tail-risk project. The dotted line is the price of the tail-risk project as a function of the population of low-ability managers.

managers invest in tail-risk projects in this economy with the benchmark parameters.

These results show low-ability managers invest in tail-risk projects even when its current-period expected return is less than its price, and the equilibrium price of the tail-risk project will be greater than its expected return. These findings are similar to the findings from previous papers which examine how career concerns affect manager preferences for assets with tail risk. Guerrieri and Kondor (2012), Makarov and Plantin (2015), and Malliaris and Yan (2015) all find low-ability managers with career concerns prefer projects with tail risk because it reduces their chance of being fired, and this preference can drive the price of assets with tail risk above its fundamental value.

With the low-ability manager's policy function, the dynamic properties of the economy can be analyzed. I simulate the economy with different patterns of shocks to examine how output and assets under management evolve over time. These simulations feature boom-bust cycles in output and in the price of tail-risk projects where longer booms lead to larger crashes. Assets under management also rise during booms and fall sharply during crashes.

First, I simulate the economy with 100 periods of good shocks to examine how the economy evolves during booms (see Table 3.2). The population of low-ability managers is initialized at its lowest attainable level $(1 - \lambda)n = 0.0394$, which represents only the low-ability managers who newly entered the economy during the evening of the previous period. The population of low-ability managers N^L grows with the number of good shocks. The steady-state population of low-ability managers if the tail-risk project did not exist is 0.0721. The population of low-ability managers in this economy exceeds that level after just one period with a good shock. The growth rate decreases as the population of low-ability managers increases. With a large number of consecutive good shocks, N^L converges to 0.1618. This is lower than the threshold of $N^L = 0.2272$ where low-ability managers mix between the risky and tail-risk project. As such, all low-ability managers invest in a tail-risk project in this economy.

For any population of low-ability managers, the presence of the tail-risk project produces an ex-ante expected output (expected output before the shock is realized) that is lower than the steady-

Table 3.2: Simulated economy with only good shocks

Period	1	2	3	4	5	100
Low-ability manager pop. (N^L)	0.0394	0.0746	0.1032	0.1243	0.1387	0.1618
Fraction choose tail-risk project (D)	100%	100%	100%	100%	100%	100%
Price of tail-risk project (c^T)	1.023	1.043	1.059	1.071	1.079	1.093
Expected output	1.056	1.054	1.051	1.048	1.046	1.043
Output with good shock	1.066	1.072	1.076	1.078	1.080	1.081
Output with bad shock	1.017	0.982	0.953	0.932	0.918	0.895

Notes: This table shows how the population of low-ability managers and the price of tail-risk project evolve with consecutive periods of good shocks. The economy is simulated with the benchmark parameter values in Table 3.1. The population of low-ability managers is initialized with only the new entrants from the evening of the previous period. The population of low-ability managers is counted in the morning of each period, before firing decision and new entrants for that period. The expected output per saver is the expected return per saver across all matched and unmatched savers before the shock is realized. The output per saver entries for the good and bad shocks are the average outputs conditional on the appropriate shock being drawn, where their average weighted by the probability of each shock occurring is the expected output per saver.

state output of 1.057 if the tail-risk project did not exist. This occurs because low-ability managers that invest in a risky project generate returns equal to that of the risk-free asset. As such, if the tail-risk project did not exist, the population of low-ability managers would not affect the expected output. The expected output will be lower with any amount of investment in tail-risk projects.

As the number of consecutive good shocks grows, the ex-ante expected output per saver in the economy (expected output before the shock is realized) decreases. This decline happens for two reasons. First, the population of low-ability managers grows. Since all low-ability managers invest in a tail-risk project in equilibrium and tail-risk projects have a lower expected return than that of the risk-free asset, a larger number of savers delegating to low-ability managers directly reduces the ex-ante expected output. Second, the price of the tail-risk project increases with its quantity. As such, the return of tail-risk projects and thus the return generated by each low-ability manager decreases with the population of low-ability managers. When the population of low-ability managers approaches its highest level, the ex-ante expected output per saver of the economy approaches being 1.3% smaller than the steady-state output if the tail-risk project did not exist.

While the ex-ante expected output per saver decreases with the population of low-ability managers, the output conditional on a good shock occurring increases with the population of low-ability managers. With the benchmark parameter values, the increase in output from replacing savers investing in the risk-free project with low-ability managers investing in a tail-risk project outpaces the decrease in output from the higher price of the tail-risk project. Because of this offsetting factor, the output after a good shock converges very quickly to its maximum value. There are only small increases to the output per saver conditional on a good shock after the second period of consecutive good shocks. In contrast, the decline in the output after a bad shock is much larger and approaches its maximum value more gradually as the number of consecutive good shocks increases.

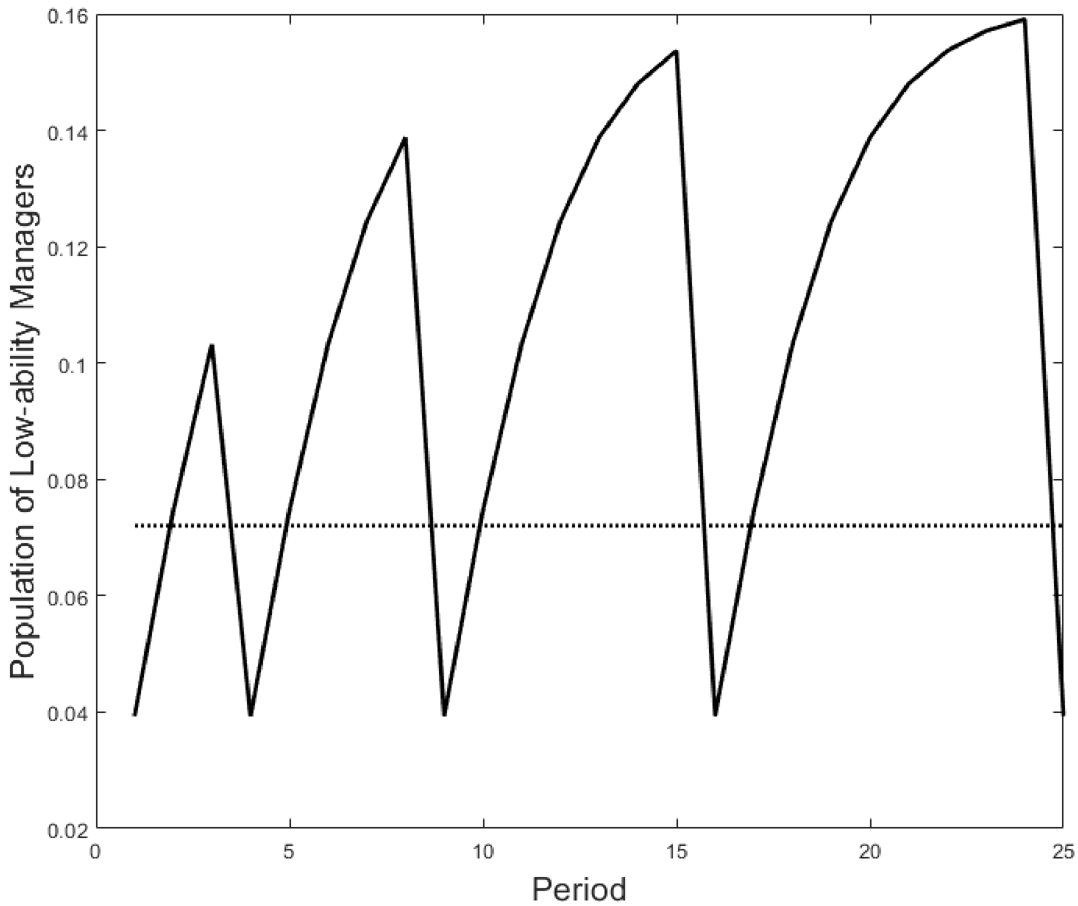
Next, I simulate the economy with random shocks over a large number of periods to examine the long-run properties of this model. The economy is simulated for 10,000 periods, and the first 100 periods are thrown out to remove the effects of the initial conditions.[8] On average, the population of low-ability managers is 0.1001. The average output of this economy across all periods is 1.049. This average output is higher than the output from saving in the risk-free asset, but is lower than the steady-state output per saver of 1.057 if the tail-risk model did not exist. Over the long run, the existence of the tail-risk project reduces per-period output by 1.3% compared to when delegated investment management exists without the tail-risk project. As shown Section 3.5, certain sets of parameter values can generate outcomes where delegated investment management reduces the long-run average output below that of the returns from saving.

This economy generates an average peak-to-trough decline in output or returns of 13.4%. These declines are high compared to the average peak-to-trough decline in output during contractions in the US from 1947-2015 of 6.4% (Cociuba et al., 2016). However, declines of these magnitudes are not uncommon in asset returns. For example, Barro and Ursúa (2017) find 8 examples where U.S. stock market returns declined by more than 25%, although many of these declines occurred over a multi-year period. The maximum peak-to-trough decline this model can generate is 17.2%, but this model does not include any features that could further amplify the effects of a shock.

Finally, to examine how the economy responds to shorter and longer booms, I simulate an

[8]Throwing out 100 periods is sufficient to remove the effects of the initial conditions. When the population of low-ability managers is low such that all low-ability managers invest in a tail-risk project, all low-ability managers are fired after a single bad shock, after which the effects of the initial conditions are removed. For economies where low-ability managers mix between investing in a risky project and tail-risk project in equilibrium, two bad shocks occurring close together would be sufficient to remove the effects of the initial conditions.

Figure 3.2: Population of low-ability managers in simulated economy

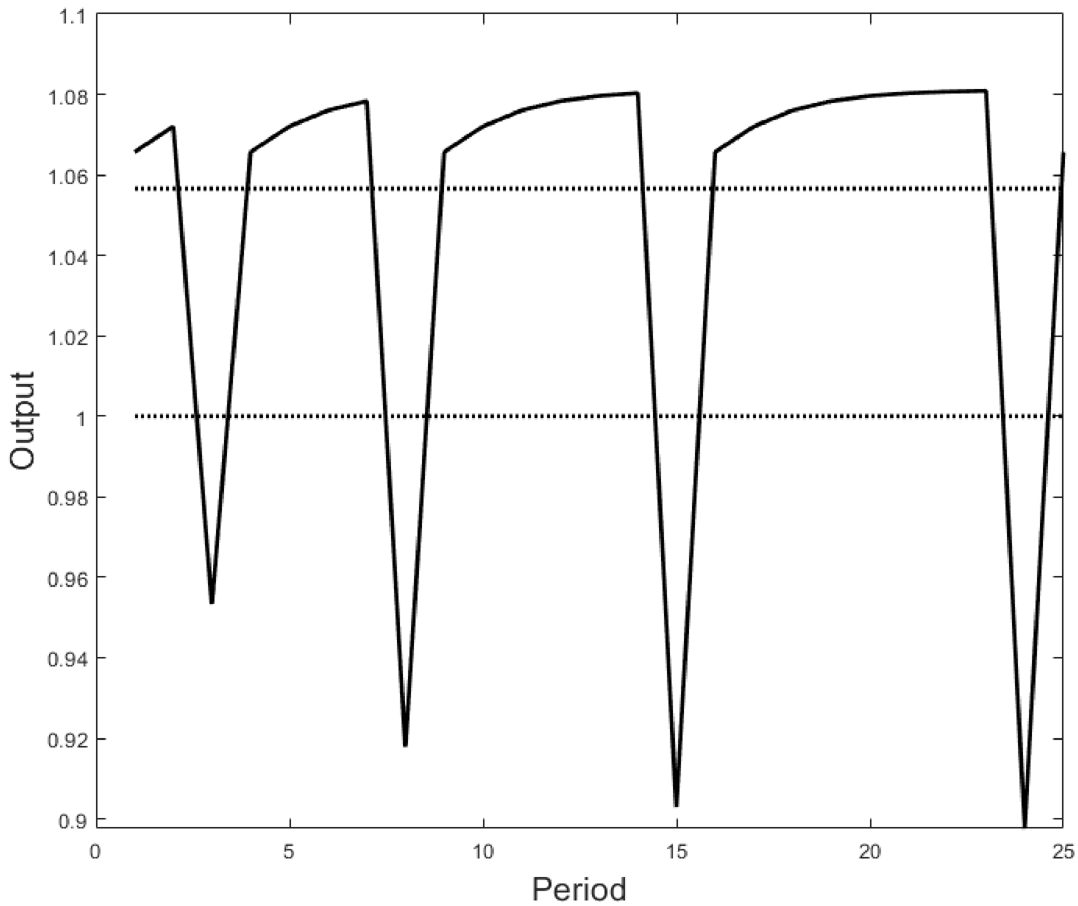


Notes: This figure shows the population of managers in the morning of each period as a fraction of the population of savers in the simulated economy where a bad shock occurs after 2, 4, 6, and 8 periods of consecutive good shocks. The benchmark parameter values in Table 3.1 are used for this simulation. The solid line represents the population of low-ability managers as a fraction of savers. For comparison, the steady-state population of low-ability managers if they invested only in risky projects is shown as the dotted line.

economy which experiences a bad shock after 2, 4, 6, and 8 periods of consecutive good shocks. Figure 3.2 shows how the population of low-ability managers N^L evolves given this pattern of shocks. The solid line shows the population of low-ability managers in this economy. For comparison, the dotted line in the figure represents the long-run steady state population of low-ability managers if they only invested in risky projects, which is 7.2% with the benchmark parameters.

The population of low-ability managers N^L increases with the number of consecutive good shocks. It quickly exceeds the steady-state population of low-ability managers if they invested in risky projects. The population falls sharply after bad shocks. Since all low-ability managers invest

Figure 3.3: Average output in simulated economy



Notes: This figure shows the output per saver in the simulated economy where a bad shock occurs after 2, 4, 6, and 8 periods of consecutive good shocks. The benchmark parameter values in Table 3.1 are used for this simulation. The lower dotted line at 1 represents the average output if savers invested in the risk-free asset instead of delegating to investment managers. The top dotted line at represents the average steady-state output where low-ability managers invest only in risky projects.

in a tail-risk project in equilibrium, all low-ability managers are revealed and fired after a bad shock. Increases in the population of low-ability managers coincide with increases in assets under management. The behavior of assets under management before and after crashes in this model is similar to the increase in assets under management leading up to the 2007 financial crisis and the decline after the crash (e.g., Statista (2020), Gerakos et al. (2016)).

The dynamics of the population of low-ability managers generate boom-bust cycles with larger declines in output if a crash occurs after longer booms. Figure 3.3 graphs the output for this simulation. For comparison, the output if all savers invested in the risk-free asset (lower dotted line) and the steady-state output if all low-ability managers invested in risky projects (upper dotted line) are also shown. The drop in output is larger for crashes that occur after longer booms because the previous period's output is higher and because output falls to a lower value after the crash.

These results show boom-bust cycles similar to those described by Minsky (1992) can be generated through just delegated investment management and assets with correlated tail risk. Unlike models which generate boom-bust cycles based on learning (e.g., Bhattacharya et al. (2015)), managers being fully informed about the return distribution of assets does not prevent these boom-bust cycles. Further, this model shows that boom-bust cycles do not require changes in the return distributions of assets such as a sudden increase in the riskiness of an asset. Finally, these findings suggest a possible mechanism that can explain changes in assets under management during boom-bust cycles.

3.5 Robustness and Comparative Statics

I repeat the exercises conducted in Section 3.4 with different parameter values. For these exercises, I examine the effects of changing one subset of variables while holding the other variables at their benchmark levels in Table 3.1.

An equilibrium is found in each of these exercises, which shows the existence of the equilibrium is not reliant on a specific set of parameter values. With most sets of parameter values, the model continues to generate economies with boom-bust cycles where the size of the crash increases with the duration of the boom, along with assets under management increasing during booms and sharply declining after a crash. The exceptions are parameter values where the population of low-ability managers very quickly reaches its maximum attainable value. In these scenarios, the size of the crash increases only minimally past a small number of consecutive good shocks.

Some features of these economies with alternate parameter values differ from those in the economy with the benchmark parameters. With the benchmark values, low-ability managers always invest in a tail-risk project in equilibrium. In several sets of alternate parameter values considered, there are scenarios in equilibrium where low-ability managers play a mixed strategy in choosing whether to invest in a tail-risk project or in a risky project. Examples of these sets of parameter values include ones with decreases in the discount factor β, decreases in the probability of the bad shock ϕ, increases in the slope coefficient on the price of the tail-risk project γ, and increases in the population of entering managers n. However, large changes in these variables are often required to generate an equilibrium where low-ability managers mix between the risky and tail-risk projects for attainable populations.

With the benchmark parameters and almost all sets of parameter values examined, delegated investment management still improves output on average compared to if savers only invested in the risk-free asset. By decreasing the fraction of high-ability managers among new managers λ by a very large amount, it's possible for the average return with delegated investment management to be below that of saving in the risk-free asset.

I first examine the effect of changing the discount factor β (see Table 3.3). The benchmark discount factor is $\beta = .95$, and I consider $\beta = .99$, $\beta = .5$, and $\beta = .2$. Changes in β affect the manager's continuation values of being retained. Increases in β increase the price threshold before low-ability managers become indifferent between investing in a risky project and investing in a tail-risk project, while decreases in β have the opposite effect. With the benchmark parameter values, low-ability managers always prefer investing in a tail-risk project in equilibrium. As such, the only changes in β that affect equilibrium outcomes are decreases which are large enough to cause low-ability managers to mix between investing in a risky project and investing in a tail-risk project.

As seen by the results of this exercise, even a decrease in β to .5 is not sufficient to achieve this outcome. A decrease of β to .2 does generate an equilibrium where low-ability managers mix between investing in a risky project and investing in a tail-risk project. Such a large decrease in β would also eliminate the boom-bust cycles. While the population of low-ability managers still increase after good shocks and decrease after bad shocks when $\beta = .2$, the assets invested in tail-risk projects quickly converges to its maximum value and losses in a crash thus quickly stop increasing with additional periods of good shocks. This result emphasizes that the low-ability manager's career concerns are the mechanism that generate boom-bust cycles in this economy.

Table 3.3: Comparative statics: discount factor β

	benchmark $\beta = .95$	$\beta = .99$	$\beta = .5$	$\beta = .2$
Low-Ability Manager Population				
steady-state N^L w/o tail-risk	0.0721	0.0721	0.0721	0.0721
minimum N^L in equilibrium	0.0394	0.0394	0.0394	0.0394
mean N^L in equilibrium	0.1001	0.1001	0.1001	0.0997
maximum N^L in equilibrium	0.1618	0.1618	0.1618	0.1335
Low-Ability Manager Investment Decisions				
N^L when managers first mix	0.2273	0.2305	0.1649	0.0860
c^T when managers first mix	1.1300	1.1318	1.0942	1.0491
minimum D^L in equilibrium	1	1	1	0.647
Output				
steady-state output w/o tail-risk	1.057	1.057	1.057	1.057
long-run mean output	1.049	1.049	1.049	1.053
mean peak-to-trough decline	-13.4%	-13.4%	-13.4%	-9.4%
maximum peak-to-trough decline	-17.2%	-17.2%	-17.2%	-9.6%
Decline in output				
bad shock after 2 good shocks	-11.1%	-11.1%	-11.1%	-9.5%
bad shock after 4 good shocks	-14.9%	-14.9%	-14.9%	-9.6%
bad shock after 6 good shocks	-16.4%	-16.4%	-16.4%	-9.6%
bad shock after 8 good shocks	-17.0%	-17.0%	-17.0%	-9.6%

Next, I examine the effects of variables which directly affect the population of managers. The first variable of this category considered is the exogenous separation rate δ (see Table 3.4. The benchmark is $\delta = .06$, which is associated with low-ability managers being 24.8% of steady-state investment manager populations if the tail-risk project does not exist. I consider $\delta = .12$ and $\delta = .03$, which is associated with low-ability managers making up 38.5% and 14.5% of steady-state manager populations, respectively, when the tail-risk project does not exist. Because exogenous separation is the only way high-ability managers exit the model while low-ability managers exit the model both through exogenous separation and endogenous firings, an increase (decrease) in δ

will increase (decrease) the ratio of low-ability managers to total managers in the population.

Table 3.4: Comparative statics: exogenous separation chance δ

	benchmark $\delta = .06$	$\delta = .12$	$\delta = .03$
Low-Ability Manager Population			
steady-state N^L w/o tail-risk	0.0721	0.0685	0.0741
minimum N^L in equilibrium	0.0394	0.0394	0.0394
mean N^L in equilibrium	0.1001	0.0931	0.1038
maximum N^L in equilibrium	0.1618	0.1442	0.1711
Low-Ability Manager Investment Decisions			
N^L when managers first mix	0.2273	0.2250	0.2279
c^T when managers first mix	1.1300	1.1287	1.1303
minimum D^L in equilibrium	1	1	1
Output			
steady-state output w/o tail-risk	1.057	1.028	1.113
long-run mean output	1.049	1.022	1.105
mean peak-to-trough decline	-13.4%	-12.7%	-13.2%
maximum peak-to-trough decline	-17.2%	-15.9%	-17.2%
Decline in output			
bad shock after 2 good shocks	-11.1%	-10.8%	-10.8%
bad shock after 4 good shocks	-14.9%	-14.1%	-14.7%
bad shock after 6 good shocks	-16.4%	-15.3%	-16.4%
bad shock after 8 good shocks	-17.0%	-15.7%	-16.9%

The exogenous separation rate δ has a similar effect to the discount factor β in that it affects the continuation values and thus the price threshold where low-ability managers begin to mix between investing in a risky project and investing in a tail-risk project. However, changes in δ also affect the populations of both low-ability and high-ability managers. An increase in δ reduces the population of managers and thus average output. Interestingly, changes in δ have an ambiguous effect on the mean and maximum peak-to-trough decline in output. This likely occurs because an increase in δ decreases the population of low-ability managers and thus decreases the absolute decline in output (the numerator of the percentage decline in output), but an increase in δ also decreases the population of high-ability managers and thus decreases the pre-crash output (the denominator of the percentage decline in output).

Next, I consider changes in the number of new managers entering each period n (see Table 3.5). The benchmark is $n = 0.525$, which corresponds with a fraction of assets under management at 29% in the steady state with no tail-risk project. I consider $n = .105$ and $n = .0263$, which corresponds with assets under management of 58.2% and 14.5%, respectively, in the steady state with no tail-risk project.

Table 3.5: Comparative statics: new entering managers n

	benchmark $n = .0525$	$n = .105$	$n = .0263$
Low-Ability Manager Population			
steady-state N^L w/o tail-risk	0.0721	0.1442	0.0360
minimum N^L in equilibrium	0.0394	0.0787	0.0197
mean N^L in equilibrium	0.1001	0.1742	0.0554
maximum N^L in equilibrium	0.1618	0.2393	0.1080
Low-Ability Manager Investment Decisions			
N^L when managers first mix	0.2273	0.2271	0.2278
c^T when managers first mix	1.1300	1.1298	1.1303
minimum D^L in equilibrium	1	0.952	1
Output			
steady-state output w/o tail-risk	1.057	1.113	1.028
long-run mean output	1.049	1.095	1.026
mean peak-to-trough decline	-13.4%	-20.0%	-8.1%
maximum peak-to-trough decline	-17.2%	-22.3%	-12.2%
Decline in output			
bad shock after 2 good shocks	-11.1%	-18.9%	-6.0%
bad shock after 4 good shocks	-14.9%	-22.2%	-8.8%
bad shock after 6 good shocks	-16.4%	-22.2%	-10.4%
bad shock after 8 good shocks	-17.0%	-22.3%	-11.3%

As expected, increases in n increase the equilibrium populations of both low-ability and high-ability managers. The increase in the population of high-ability managers increases the equilibrium output variables, and the increase in the population of low-ability managers increases the size of the peak-to-trough declines.

Increases in n can also create scenarios where low-ability managers are indifferent between investing in a risky project and investing in a tail-risk project in equilibrium. The low-ability manager's value function is decreasing in the population of low-ability managers, and an increase n increases the growth rate of low-ability managers. As such, an increase in n decreases the continuation value of being retained and thus lowers the price threshold for when low-ability managers mix between investing in a risky project and investing in a tail-risk project. Combined with its direct effect of increasing manager populations, the equilibrium population of low-ability managers can exceed the threshold where they become indifferent between investing in a risky project and investing in a tail-risk project with a sufficiently large increase in n.

While an increase in n increases the peak-to-trough declines after a crash, it can limit how much these declines increase with additional periods of good shocks. When n is high, the population of low-ability managers approaches its maximum attainable value more quickly. Additionally, peak-to-trough declines grow more slowly after the point where managers begin mixing between investing in a risky project and investing in a tail-risk project. While the model still produces slightly larger crashes after longer booms with a high n, this effect becomes negligible after the boom exceeds a small number of consecutive good shocks.

The last variable which directly affects the population of managers is the fraction of new managers that have high ability λ (see Table 3.6). The benchmark is $\lambda = .25$, which corresponds with new managers generating average returns of 1.065 if they invested only in a risky project. I consider $\lambda = .35$, $\lambda = .06$, and $\lambda = .02$, which corresponds with average returns for new managers of 1.091, 1.016, and 1.005, respectively, if they invested in a risky project.[9] Changes in λ also affect the fraction of managers with low ability in the steady state where the tail-risk project does not exist. That fraction is 16.9%, 63.2%, and 84.3%, respectively, for $\lambda = .35$, $\lambda = .06$, and $\lambda = .02$, compared to a fraction of 24.8% in the benchmark scenario.

Changes in λ affect the proportions of high-ability and low-ability managers in equilibrium. Increases in λ decrease the population of low-ability managers and increase the population of

[9]For the case of $\lambda = .02$, the manager's fee was also decreased to $\tau = .002$ to ensure savers would delegate to a newly-matched manager. The manager's fee τ otherwise has no effect on the equilibrium.

Table 3.6: Comparative statics: fraction of new managers with high ability λ

	benchmark $\lambda = .25$	$\lambda = .35$	$\lambda = .06$	$\lambda = .02$
Low-Ability Manager Population				
steady-state N^L w/o tail-risk	0.0721	0.0625	0.0904	0.0942
minimum N^L in equilibrium	0.0394	0.0341	0.0493	0.0514
mean N^L in equilibrium	0.1001	0.0889	0.1203	0.1244
maximum N^L in equilibrium	0.1618	0.1491	0.1839	0.1883
Low-Ability Manager Investment Decisions				
N^L when managers first mix	0.2273	0.2275	0.2267	0.2266
c^T when managers first mix	1.1300	1.1301	1.1296	1.1295
minimum D^L in equilibrium	1	1	1	1
Output				
steady-state output w/o tail-risk	1.057	1.079	1.014	1.005
long-run mean output	1.049	1.073	1.004	0.994
mean peak-to-trough decline	-13.4%	-11.8%	-16.3%	-16.9%
maximum peak-to-trough decline	-17.2%	-15.7%	-20.2%	-20.8%
Decline in output				
bad shock after 2 good shocks	-11.1%	-9.5%	-14.1%	-14.7%
bad shock after 4 good shocks	-14.9%	-13.1%	-18.2%	-18.9%
bad shock after 6 good shocks	-16.4%	-14.7%	-19.6%	-20.3%
bad shock after 8 good shocks	-17.0%	-15.3%	-20.0%	-20.6%

high-ability managers. Those effects cause the output variables to increase with λ. Peak-to-trough declines decrease with λ because fewer assets are invested in tail-risk projects. Like changes in n, changes in λ also have a small effect on the price threshold where low-ability managers become indifferent between investing in a risky project and investing in a tail-risk project. Increases in λ reduce the growth rate of low-ability managers after good shocks, and as such increase the threshold where low-ability managers become indifferent between investing in a risky project and investing in a tail-risk project.

The remaining variables examined are ones which affect the returns of projects. I first consider changes in the probability of the bad shock ϕ (see Table 3.7). Changes in ϕ require changing ρ_H in the same direction to keep the expected output of tail-risk projects equal to that of risky projects. The benchmark uses $\phi = .205$ and $\rho_H = 1.02$, which corresponds with an average length of booms of 4.87 periods. Here, I also consider $\phi = .308$ (average boom of 3.24 periods), $\phi = .257$ (average boom of 3.89 periods), $\phi = .138$ (average boom of 7.26 periods), and $\phi = .068$ (average boom of 14.75 periods). The changes in ρ_H associated with these changes in ϕ also have a dramatic effect on the probability that a low-ability manager investing in a risky project is endogenously fired. The benchmark values imply a firing probability of 51.7%, and it ranges from 89.1% to 14.5% with these alternate parameters.

Overall, increases in ϕ and ρ_H decreases the growth rate of the population of low-ability managers N^L in equilibrium. This occurs because a higher ρ_H means that for any given price of the tail-risk project, the low-ability manager has a higher chance of generating a return below ρ_H and being endogenously fired when investing in a tail-risk project even after good shocks.

However, the effect of ϕ and ρ_H on peak-to-trough declines is ambiguous. Decreases in ϕ and ρ_H initially increase peak-to-trough declines, but further decreases in can dampen them. The initial increase in peak-to-trough declines occurs both because of the higher population of low-ability managers and thus assets invested in tail-risk projects, and also because the average return of high-ability managers investing in risky projects and low-ability managers investing in tail-risk projects during good shocks is lower. The reversal in the effect of declines in ϕ and ρ_H likely occurs when

Table 3.7: Comparative statics: probability of bad aggregate shock ϕ

	benchmark $\phi = .205$ $\rho_H = 1.02$	$\phi = .308$ $\rho_H = 1.39$	$\phi = .257$ $\rho_H = 1.19$	$\phi = .138$ $\rho_H = .82$	$\phi = .068$ $\rho_H = .65$
Low-Ability Manager Population					
steady-state N^L w/o tail-risk	0.0721	0.0439	0.0555	0.1093	0.2001
minimum N^L in equilibrium	0.0394	0.0394	0.0394	0.0394	0.1045
mean N^L in equilibrium	0.1001	0.0598	0.0817	0.1286	0.2038
maximum N^L in equilibrium	0.1618	0.0715	0.1241	0.2038	0.2572
Low-Ability Manager Investment Decisions					
N^L when managers first mix	0.2273	0.1058	0.2091	0.1964	0.1344
c^T when managers first mix	1.1300	1.0605	1.1195	1.1123	1.0768
minimum D^L in equilibrium	1	1	1	0.989	0.567
Output					
steady-state output w/o tail-risk	1.057	1.097	1.076	1.035	1.016
long-run mean output	1.049	1.095	1.071	1.023	1.006
mean peak-to-trough decline	-13.4%	-8.3%	-11.5%	-15.6%	-13.6%
maximum peak-to-trough decline	-17.2%	-8.8%	-14.1%	-19.7%	-13.9%
Decline in output					
bad shock after 2 good shocks	-11.1%	-8.7%	-10.8%	-11.0%	-10.8%
bad shock after 4 good shocks	-14.9%	-8.8%	-13.4%	-15.6%	-13.4%
bad shock after 6 good shocks	-16.4%	-8.8%	-13.9%	-18.0%	-13.6%
bad shock after 8 good shocks	-17.0%	-8.8%	-14.1%	-19.3%	-13.8%

these decreases cause the population of low-ability managers to exceed the thresholds where they become indifferent between investing in a risky project and a tail-risk project in equilibrium. The boom-bust cycles where longer booms lead to larger busts is dampened when ϕ and ρ_H becomes either too large or too small.

Finally, I consider changes in the slope coefficient of the price of the tail-risk project γ. The benchmark value is $\gamma = .572$, which corresponds with a maximum price of 1.093 for the tail-risk project in equilibrium.[10] I consider three alternate values of $\gamma = 2.5$, $\gamma = 1$, and $\gamma = 0.25$, which correspond with maximum equilibrium prices of 1.139, 1.267, and 1.057, respectively.

Table 3.8: Comparative statics: slope coefficient of price of tail-risk project γ

	benchmark $\gamma = .572$	$\gamma = 2.5$	$\gamma = 1$	$\gamma = .25$
Low-Ability Manager Population				
steady-state N^L w/o tail-risk	0.0721	0.0721	0.0721	0.0721
minimum N^L in equilibrium	0.0394	0.0394	0.0394	0.0394
mean N^L in equilibrium	0.1001	0.0776	0.0894	0.1125
maximum N^L in equilibrium	0.1618	0.0935	0.1267	0.2278
Low-Ability Manager Investment Decisions				
N^L when managers first mix	0.2273	0.0545	0.1289	0.5212
c^T when managers first mix	1.1300	1.1361	1.1288	1.1303
minimum D^L in equilibrium	1	0.596	1	1
Output				
steady-state output w/o tail-risk	1.057	1.057	1.057	1.057
long-run mean output	1.049	1.050	1.048	1.052
mean peak-to-trough decline	-13.4%	-5.8%	-11.3%	-16.0%
maximum peak-to-trough decline	-17.2%	-5.8%	-13.2%	-24.7%
Decline in output				
bad shock after 2 good shocks	-11.1%	-5.8%	-10.3%	-11.7%
bad shock after 4 good shocks	-14.9%	-5.8%	-12.6%	-17.2%
bad shock after 6 good shocks	-16.4%	-5.8%	-13.1%	-20.6%
bad shock after 8 good shocks	-17.0%	-5.8%	-13.2%	-22.5%

[10] Since the price of the tail-risk project is close to 1 after the crash, the amount by which the price of the tail-risk project exceeds 1 is roughly the fall in the price after a crash. Additionally, since the expected output of one tail-risk project is 1, the amount by which the price of the tail-risk project exceeds 1 can be considered its reputation premium.

The response of the tail-risk project's price to demand γ has significant effects on the growth rate of the population of low-ability managers N^L. The mean and maximum N^L decreases with γ. Additionally, a sufficiently high γ can cause prices to increase fast enough such that low-ability managers will mix between investing in a risky project and a tail-risk project in equilibrium.

An increase in the price elasticity of the tail-risk project dampens boom-bust cycles in this economy. It does so by limiting the growth rate of the population of low-ability managers. When γ is high, more low-ability managers generate returns below ρ_H and are endogenously fired even when they invest in a tail-risk project and the aggregate shock is good. Additionally, when γ is high enough, low-ability managers begin mixing between investing in a risky project and investing in a tail-risk project in equilibrium. This further limits the growth in assets invested in tail-risk projects over time.

Overall, these exercises show the main findings of the benchmark model are robust to alternate parameters. Most sets of parameter values generated boom-bust cycles where longer booms lead to larger crashes in output. These boom-bust cycles also exhibited increases in the population of managers and thus assets under management during booms and sharp declines after crashes.

3.6 Conclusion

This paper shows delegated investment management and assets with correlated tail risk can generate boom-bust cycles in output similar to those described by Minsky (1992). These boom-bust cycles also exhibit increases in assets under management during the boom and sharp declines following a crash. The career concerns of low-ability managers are responsible for these boom-bust cycles. Low-ability managers prefer to invest in assets with tail risk to reduce their chances of being fired. During a boom when the tail risk event is not realized, fewer low-ability managers are fired and the population of low-ability managers grows. As such, more capital is invested in assets with tail risk after a longer boom, which leads to a larger crash when the tail event occurs.

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Appendix A

Chapter 1 Appendixes

A.1 Variable Definitions

2-Year Cumulative Returns

$$CumulativeReturn_{i,t+1,t+24} = \left[\sum_{\tau=t+1}^{t+24} (MonthlyReturn_{i,\tau})\right]$$

2-Year Buy-And-Hold Returns

$$BuyHoldReturn_{i,t+1,t+24} = \left[\prod_{\tau=t+1}^{t+24} (1 + MonthlyReturn_{i,\tau})\right] - 1$$

Change in Shares Outstanding

$$AdjShares_{i,\tau} = SharesOutstanding_{i,\tau} * CumulativeFactor_{i,\tau}$$

$$\%ChangeShares_{i,t} = (AdjShares_{i,t} - AdjShares_{i,t-3})/AdjShares_{i,t-3}$$

Size. Size is constructed as the log of market capitalization:

$$Size_{i,t} = \ln(Price_{i,t} * SharesOutstanding_{i,t})$$

Book-to-Market. The book-to-market ratio is calculated as the log of quotient of the book market of common equity and the market capitalization:

$$BookToMarket_{i,t} = \ln(BookValueCommonEquity_{i,t}/(Price_{i,t} * SharesOutstanding_{i,t}))$$

Momentum. I use the prior 6-month holding period returns as a proxy for momentum.

$$Momentum_{i,t} = \left[\prod_{\tau=t-5}^{t}(1 + return_{i,\tau})\right] - 1$$

A.2 Appendix: Binned Regression Coefficients

Table A.1: Coefficients on repurchase and issuance bins, 1975-2017

Centiles	Repurchase	Issuance
0-5	0.0319**	0.0263*
	(0.0133)	(0.0149)
5-10	0.0371***	0.034**
	(0.0138)	(0.0138)
10-15	0.0375**	0.0278**
	(0.0171)	(0.0138)
15-20	0.0681***	0.0422***
	(0.0172)	(0.0113)
20-25	0.0427**	0.0425***
	(0.0184)	(0.0116)
25-30	0.0665***	0.0391***
	(0.0197)	(0.0126)
30-35	0.0696***	0.0466***
	(0.0176)	(0.0125)
35-40	0.0876***	0.0426***
	(0.0205)	(0.0121)
40-45	0.0742***	0.0438***
	(0.0203)	(0.0126)
45-50	0.0749***	0.04***
	(0.0216)	(0.0117)
50-55	0.0845***	0.0509***
	(0.0199)	(0.0116)
55-60	0.0738***	0.0438***
	(0.0197)	(0.0125)
60-65	0.084***	0.0398***
	(0.0208)	(0.0119)
65-70	0.075***	0.0313**
	(0.0194)	(0.013)
70-75	0.0683***	0.0127
	(0.0214)	(0.0136)
75-80	0.0758***	-0.0158
	(0.0164)	(0.0145)
80-85	0.0591***	-0.0419***
	(0.0172)	(0.0132)
85-90	0.0458***	-0.0623***
	(0.016)	(0.012)
90-95	0.0142	-0.0837***
	(0.015)	(0.014)
95-100	-0.0581**	-0.116***
	(0.023)	(0.0154)

Notes: This table lists the coefficients on the binned regressions for the full sample. The centiles in each bin are shown on the left. See Table 1.6 for the coefficients on the firm controls.

Appendix B

Chapter 2 Appendixes

B.1 Variable Definitions

2-Year Excess Return over Equal-Weight Portfolio

The 2-year excess return over the equal-weight portfolio of firm i for month t is calculated by summing the difference between the monthly return of firm i and the return of the CRSP equal-weight portfolio over 24 months.

$$ExReturn_{i,t+1,t+24} = \sum_{\tau=t+1}^{t+24} (r_{i,\tau} - r_{ew,\tau}) \tag{B.1}$$

1-Quarter Change in Shares Outstanding

The one-quarter change in shares outstanding is the percent change in adjusted shares outstanding over 3 months. Shares outstanding are adjusted to remove the effect of stock splits by multiplying the number of shares outstanding by CRSP's cumulative factor to adjust shares.

$$ChangeShares_{i,t} = \frac{AdjShares_{i,t} - AdjShares_{i,t-3}}{AdjShares_{i,t-3}} \tag{B.2}$$

$$AdjShares_{i,t} = Shares_{i,t} * CFacShares_{i,t} \tag{B.3}$$

Size

Size is calculated as the natural log of the stock's market capitalization.

$$Size_{i,t} = \ln(Price_{i,t} * Shares_{i,t}) \tag{B.4}$$

Book-To-Market

Book-to-market is calculated as the natural log of the firm's book value of common equity (from Compustat) divided by its stock market capitalization.

$$BookMarket_{i,t} = \ln(\frac{BookValueCommonEquity_{i,t}}{Price_{i,t} * Shares_{i,t}}) \tag{B.5}$$

Momentum

Momentum is proxied using the prior 6-month return.

$$Momentum_{i,t} = \sum_{\tau=t-6}^{t-1} (r_{i,\tau}) \tag{B.6}$$

B.2 Summary Statistics

Table B.1: Summary statistics, share codes 10-11, 2003-2017

	Mean	SD	1%	25%	50%	75%	99%	N
Key Variables								
Return	0.23	0.69	-1.92	-0.08	0.25	0.57	2.31	211940
ChangeShares	0.01	0.06	-0.06	0.00	0.00	0.01	0.34	211940
Repurchases	0.01	0.02	0.00	0.00	0.01	0.02	0.12	48437
Issuances	0.02	0.08	0.00	0.00	0.00	0.01	0.49	134743
Controls								
Size	6.13	2.02	1.95	4.64	6.06	7.52	10.57	211940
BTM	-0.72	0.83	-3.19	-1.19	-0.64	-0.18	1.25	203828
Momentum	0.07	0.36	-0.69	-0.13	0.04	0.22	1.62	211940

Notes: This table displays the summary statistics of the variables used in this analysis for stocks with share codes 10 and 11. Return is the 2-year cumulative stock return: the sum of the monthly holding period returns over the next 24 months. ChangeShares is the one-quarter percent change in shares outstanding. Repurchase is one-quarter percent decreases in shares outstanding. Issuance is one-quarter increases in shares outstanding. Observations with zero change in shares outstanding, repurchases, and issuances are included when calculating the statistics in this table. Size is the log of the market capitalization (in millions). BTM is the book-to-market ratio: the log of the book value of common equity divided by the market capitalization. The BTM statistics exclude observations with missing book-to-market values which comprise 16.4% of the sample. Momentum is the prior 6-month buy-and-hold return.

Table B.2: Contemporaneous correlations, share codes 10-11, 2003-2017

	Return	ChangeShares	Size	BTM	MissBTM
ChangeShares	-0.053				
Size	-0.036	-0.091			
BTM	0.103	-0.041	-0.351		
MissBTM	-0.002	0.037	-0.064		
Momentum	-0.043	0.057	0.109	-0.229	-0.013

Notes: This table displays the contemporaneous correlations between the main variables, without separating the change in shares outstanding into repurchases and issuances, for stocks with share codes 10 and 11. Correlations are calculated including observations with zero change in shares outstanding. Return is the 2-year cumulative stock return: the sum of the monthly holding period returns over the next 24 months. ChangeShares is the one-quarter percent change in shares outstanding. Size is the log of the market capitalization. BTM is the book-to-market ratio: the log of the book value of common equity divided by the market capitalization. The correlations for BTM are calculated excluding observations with missing BTM values. MissBTM is the missing book-to-market indicator variable, which takes on a value of 1 if BTM is missing and is set to 0 otherwise. Momentum is the prior 6-month buy-and-hold return.

B.3 Coefficients on Binned Regressions

Table B.3: Binned regression, share codes 10-11, 2003-2017: coefficients of repurchase/issuance bins

	Repurchase	Issuance
0-5	-0.0081	0.0039
	(0.0228)	(0.0235)
5-10	-0.0055	0.0092
	(0.0214)	(0.0248)
10-15	-0.0097	-0.009
	(0.022)	(0.0202)
15-20	0.0004	-0.0045
	(0.019)	(0.023)
20-25	0.0217	0.0196
	(0.0197)	(0.0239)
25-30	-0.0195	0.0172
	(0.0199)	(0.0164)
30-35	0.0295*	0.0044
	(0.017)	(0.0198)
35-40	0.0235	0.0106
	(0.0178)	(0.0212)
40-45	0.0075	0.0207
	(0.0143)	(0.0149)
45-50	0.0203	0.0075
	(0.0247)	(0.0229)
50-55	-0.0111	0.0329
	(0.0251)	(0.0219)
55-60	0.021	0.0205
	(0.0207)	(0.0188)
60-65	0.0178	0.0173
	(0.0181)	(0.026)
65-70	0.0082	0.0177
	(0.0179)	(0.0252)
70-75	0.0167	0.0188
	(0.0211)	(0.0218)
75-80	0.0248	0.0017
	(0.0216)	(0.0183)
80-85	0.001	-0.0104
	(0.0217)	(0.0281)
85-90	0.0168	-0.0342
	(0.0207)	(0.0216)
90-95	0.0285*	-0.119***
	(0.0164)	(0.0175)
95-100	0.0123	-0.145***
	(0.0168)	(0.0284)

Notes: This table shows the coefficients on the binned regression with repurchase and issuance bins performed in Section 2.3.2, for stocks with share codes 10-11.

Table B.4: Binned regression, share codes 12-75, 2003-2017: coefficients of repurchase/issuance bins

	Repurchase	Issuance
0-5	0.0357*	0.0112
	(0.021)	(0.0216)
5-10	0.0546**	0.0151
	(0.0251)	(0.0137)
10-15	0.0532***	-0.0014
	(0.0179)	(0.0086)
15-20	0.0546**	0.0122
	(0.027)	(0.0113)
20-25	0.0339*	0.024
	(0.0184)	(0.0164)
25-30	0.0375	0.0061
	(0.0227)	(0.0115)
30-35	0.0424	0.0276
	(0.0274)	(0.0215)
35-40	0.0483***	0.0268*
	(0.0175)	(0.0152)
40-45	0.0253	0.0262*
	(0.0195)	(0.0147)
45-50	0.0278	0.0294***
	(0.0247)	(0.0094)
50-55	0.0289	0.0103
	(0.0184)	(0.014)
55-60	0.0262	0.0092
	(0.0182)	(0.0156)
60-65	0.0056	0.002
	(0.0192)	(0.0155)
65-70	0.0223	-0.0123
	(0.0169)	(0.0121)
70-75	0.03*	-0.0201
	(0.0176)	(0.0153)
75-80	-0.0117	-0.027***
	(0.0218)	(0.0099)
80-85	0.0047	-0.0192
	(0.02)	(0.0207)
85-90	-0.0019	-0.0407**
	(0.023)	(0.0163)
90-95	-0.0419	-0.055**
	(0.0301)	(0.0211)
95-100	-0.0553	-0.0759**
	(0.05)	(0.0307)

Notes: This table shows the coefficients on the binned regression with repurchase and issuance bins performed in Section 2.3.2, for stocks with share codes 12-75.

Curriculum Vitae

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Post-Secondary Education and Degrees:	Ph.D., Department of Economics University of Western Ontario London, ON 2012-2020
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