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SHARE REPURCHASES: MARKET TIMING AND ABNORMAL RETURNS

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Contents

List of Figures	v
List of Tables	vi
Acknowledgements	vii
Abstract	viii
1 Introduction	1
2 Background	4
2.1 Prior literature	4
2.2 How share repurchase programs work in the U.S.	7
2.3 How I obtain monthly repurchase data	9
2.4 The distribution of repurchases	15
3 Do firms earn abnormal returns on actual repurchases?	18
3.1 Portfolios formed with one to seven month holding periods	19
3.2 Portfolios based upon NYSE market equity quintiles	21
3.3 Portfolios formed on repurchase quantile for firms with repurchase programs . . .	23
3.4 Portfolios formed at quarter end on Compustat data	25

4	When do abnormal returns occur in the quarter?	27
4.1	Computing abnormal returns	27
4.2	The timing of abnormal returns	28
4.3	The timing of abnormal returns and the relation to firm size	33
5	Forecasting share repurchases using machine learning	35
5.1	Features for forecasting	37
5.2	Machine learning regression models	37
5.3	Variable selection with LASSO	38
5.4	Selecting regularization and model hyper-parameters through cross-validation . . .	39
5.5	Out of sample forecasts	39
6	The share repurchase surprise: market reaction to unexpected repurchases	41
6.1	Can the unexpected share repurchase announcement effect significantly be linked to proxies for information asymmetry or average q ?	43
7	Is firm repurchase behavior consistent with trying to time the market?	46
7.1	Fraction of shares repurchased and prior cumulative abnormal returns	46
7.2	Evidence from the relation between repurchase fraction and price paid for repur- chases in a month	50
8	Do firms acquire shares at unusually low prices?	55
9	Conclusion	60
	Bibliography	62
A	Technical Details	66
A.1	Parser Overview	66

A.2	Matching to other data sets	67
A.3	Duplicates	67
A.4	Abnormal returns: characteristic adjusted returns	68
A.5	Abnormal returns: risk based models	68
A.6	Accurate average price data	69

List of Figures

2.1	Dividends and share repurchases for publicly listed U.S. companies	9
2.2	Excerpt from a Microsoft 10-K	10
2.3	Overview of parsing system	11
2.4	Consistency of average price paid in the quarter with Compustat	13
2.5	Distribution of share repurchases as a share of market cap	15
2.6	Share of firm quarters with positive repurchases by firm industry	16
2.7	Fraction of firm-quarters with positive repurchases pursuant to a public program .	17
3.1	Abnormal returns to share repurchases (relative to Fama-French three factor model)	20
3.2	Abnormal returns to share repurchases (relative to Fama-French five factor model) .	21
5.1	Out of sample repurchase forecast scores	40
7.1	Prior cumulative abnormal return and repurchase fraction	49
7.2	Examples of repurchase fraction vs. difference with VWAP	51
7.3	Repurchase fraction vs. diff	52
7.4	Repurchase fraction and log size vs. diff	53
7.5	Polynomial fit of repurchase fraction vs.within month return on share repurchases .	54
8.1	Difference between average repurchase price and VWAP vs.market cap	59

List of Tables

2.1	Summary statistics	12
2.2	Consistency with Compustat	14
3.1	Alphas of three month repurchase portfolios by NYSE market cap quintile	22
3.2	Portfolios by quantile of repurchase activity	24
3.3	After quarter end repurchase portfolios 1985 - 2015	26
4.1	Share repurchases and timing of abnormal returns: different models of expected returns	30
4.2	Share repurchases and timing abnormal returns	32
4.3	Share repurchases, market cap, and timing of abnormal returns	34
6.1	Share repurchases, unexpected repurchases, and abnormal returns near filing or earnings date	42
6.2	Variation of share repurchase announcement effect	45
7.1	Repurchase fraction and Fama-French three factor cumulative abnormal return in prior 30 days	48
8.1	Comparison of repurchase price to several benchmarks	57

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Abstract

Prior research shows positive abnormal returns follow the announcement of a new share repurchase program, but do firms earn abnormal returns on their actual repurchases? An obstacle to answering this question has been poor data on the timing of corporate share repurchases. I build a near complete dataset of monthly share repurchases using software I wrote to extract the data from 10-Q and 10-K filings. Constructing portfolios based upon the share repurchase signal, I find small to medium firms earn abnormal returns while large firms do not. Furthermore, I find evidence consistent with a market reaction to the disclosure of share repurchases. Firms experience positive abnormal returns around their 10-Q and 10-K filing date relative to non-repurchasers with public programs, and using machine learning techniques to forecast share repurchases, I find the share repurchase surprise, actual minus forecast repurchases, is associated with positive abnormal returns around a firm's earning announcement and 10-Q, 10-K filing dates.

My main contributions are thus threefold: I provide systematic, machine extracted data on repurchases, show that small to mid-size firms have positive abnormal returns while large firms do not, and use machine learning techniques to forecast repurchases and show abnormal returns around earning announcement days and 10-Q and 10-K filing dates are positively associated with the unexpected component of repurchases, the share repurchase surprise.

Chapter 1

Introduction

Do firms succeed in timing the market and opportunistically repurchasing undervalued shares? Or to what extent may managers be over-optimistic, repurchasing based upon miscalibrated beliefs (Ben-David et. al. 2010) over their firms future stock price? Managers overwhelmingly cite stock market undervaluation as the top reason to repurchase shares (Baker 1981, Wansley et. al. 1989, Tsetekos 1991, Graham and Harvey 2001, Baker et. al. 2003, Brav et. al. 2005). If that is indeed correct, then testing for abnormal returns on share repurchases becomes an indirect test of whether CEOs have factual or miscalibrated beliefs about their stock price. Another possibility is that survey results are dated and other reasons orthogonal to share undervaluation increasingly dominate, such as CEO compensation tied to earnings per share growth (Hribar et. al. 2016). Irrational markets or irrational management is a critical distinction in behavioral corporate finance. If markets are irrational, it may be efficient to insulate management from markets, but if management has miscalibrated beliefs, it may be efficient to subject management to market discipline (Baker et. al. 2003).

Event studies show that positive abnormal returns follow the public announcement of a share repurchase program (Vermaelen 1981, Lakonishok and Vermaelen 1990, Ikenberry et. al. 1995, Chan et. al. 2007, Peyer and Vermaelen 2009, Manconi et. al. 2015). But because of data limita-

tions as to precise timing, determining the actual returns on actual repurchases is a more difficult question. A board granting management authorization to repurchase shares can be quite different from management's actual repurchase of shares (Stephens and Weisbach 1998). Timing and quantity may differ significantly over the life a repurchase program and within a quarter. Typical data sources such as CRSP or Compustat data are quarterly and do not distinguish between publicly announced programs and other transactions (Banyi et. al. 2008).

I build on a recent literature that uses monthly share repurchase data reported in 10-Qs and 10-Ks since mid 2004 (Bozoanic 2009, De Cesari et. al. 2012, Ben-Rephael et. al. 2013, Dittmar and Field 2015). Rather than collecting limited data by hand (as prior papers did), I systematically extract nearly all repurchase data using custom software I wrote that runs on Amazon Cloud. My analysis will differs significantly from these prior papers.

I use calendar time portfolios (Fama 1998) formed monthly on the quantity of shares repurchased to rigorously test strong-form market efficiency. I find statistically significant, positive, abnormal returns for repurchasing firms but not those in the top quintile of NYSE market capitalization. Because abnormal returns vary by firm size, the average firm earns abnormal returns on share repurchases while the average dollar spent on repurchases does not. I construct an out of sample forecast of share repurchases using machine learning techniques, decompose actual repurchases into an expected and unexpected component, and show markets react to unexpected share repurchases, the share repurchase surprise, at information disclosure dates. I also show positive abnormal returns coincide with a window around the filing of a 10-Q or 10-K on SECs EDGAR for repurchasing firms. The monthly pattern of repurchase prices and quantities is consistent with many firms repurchasing shares after price declines (that are possibly perceived by management as unwarranted). Prior papers (Brockman and Chung 2001, De Cesari et. al. 2012, Ben-Rephael et. al. 2013, Dittmar and Field 2015) find firms acquire shares for exceptionally low prices within a month (compared to the volume weighted average price), but in contrast with this literature, I show that estimated discount becomes much smaller in magnitude once observations are weighted

by the fraction of market cap repurchased.

Consistent with an information or signaling story, firms earn abnormal returns on their share repurchases and markets react to disclosure of share repurchase news, but these effects are absent or smaller for firms in the top quintile of market cap, where the vast dollar value of repurchases lies.

Section 1 gives background information: a review of prior literature, how share repurchase programs work, and how I obtain my data. Section 2 uses the calendar time portfolio approach to estimate abnormal returns to actual share repurchase programs. Section 3 examines when abnormal returns occur. Section 4 constructs a share repurchase forecast, allowing me to decompose repurchases into an expected and unexpected component, the share repurchase surprise. Section 5 examines the market reaction to share repurchase surprises. Section 6 examines whether firms repurchase quantities and timing is consistent with trying to repurchase under valued shares. Section 7 examines how the estimated discount at which firms acquire shares declines when observations are weighted by the repurchased fraction of shares outstanding rather than equal weighted (as in the prior literature).

Chapter 2

Background

2.1 Prior literature

There are expansive literatures on why firms repurchase shares, how markets respond to program announcements, the acquisition prices paid for shares and short-term performance, and looking longer term, the net-issues anomaly of empirical asset pricing. My contribution lies in measuring the short-term performance of share repurchase programs with better data and in a more asset pricing centric way, particularly forming calendar time portfolios on the monthly quantity of shares repurchased. As far as I know, forecasting repurchases and showing that markets react to share repurchase surprises is entirely new.

The dominant reason given in management surveys for repurchasing shares is market undervaluation (Baker 1981, Wansley et. al. 1989, Tsetekos 1991, Graham and Harvey 2001, Baker et. al. 2003, Brav et. al. 2005). Stephens and Weisbach (1998) and Dittmar (2000) argue that repurchase behavior is consistent with firms repurchasing in response to perceived undervaluation. Also based on survey data, CEOs may believe the world looks like Garrison Keilor's fictional Lake Wobegon where "all the women are strong, all the men are good-looking, and all the children are above average." Three-quarters of surveyed CEOs believe their firms to be undervalued by public

markets (Poterba and Summers 1995).

As discussed in Dittmar (2000), other reasons to repurchase shares include to distribute free cash flow, to adjust capital structure, to defend against takeovers, and to neutralize dilution from employee share grants. More recently, CEO contracts increasingly tie compensation to earnings per share growth, creating another motive to reduce share counts. DeAngelo and Skinner (2008) argue that among all motives, distribution of free cash flow is foundational to payout policy.

On the topic of program announcement effects, Lakonishok and Vermaelen (1990) find positive abnormal returns in the two years following repurchase tender offers. Bartov (1991) suggests open-market repurchase programs signal earnings and risk changes. Ikenberry, Lakonishok, and Vermaelen (1995) construct a sample of repurchase announcements from 1980-1990 and find positive abnormal returns of 12 percent in the four years after the announcement, suggesting markets underreact to repurchase announcements. Liu and Ziebart (1997) argue there is an over-reaction to good news repurchase announcements. Fama (1998) and Mitchell and Stafford (2000) question some of the event study methodology used to establish market underreaction. Peyer and Vermaelen (2009) reject the hypothesis that the anomaly has disappeared.

Related to the long-term returns to share repurchases is the net-issues anomaly that companies with shrinking share counts have higher returns than firms with growing share counts (Pontiff and Westgate 2008, Fama and French 2008, Novy-Marx and Velikov 2016, Evgeniou et. al. 2016). The net issues puzzle originally came up in the context of long-term IPO underperformance (Ritter 1991, Loughran and Ritter 1995) but the long leg of the trade (i.e. going long firms that net repurchase shares) generates abnormal returns as well.

Wang (2009) finds positive abnormal returns to disclosure of actual share repurchases in United Kingdom data. Using US Compustat/CRSP data, Bonaime et. al. (2015) find repurchase programs underperform a smoothed strategy.

Turning to actual share repurchases, a more recent literature has hand collected data on monthly share repurchases in the US from 10-Qs and 10-Ks to examine repurchase programs more directly.

Banyi et. al. (2008) first used this data to show many CRSP or Compustat based proxies for open market repurchases differ significantly from actual, reported repurchases. Bozanic (2009) was one of the first to use the monthly data, showing companies repurchase when they have discretionary cash flow.

Using data for 265 firms for one and a half years, Cesari et. al. (2012) find two key pieces of evidence that management engages in market timing to benefit non-selling shareholders. First, they find that averaged over firm-months, the average acquisition price is unusually low, 62 basis points below the average closing price and 52 basis points the volume weighted average price of the period. Second they provide evidence that abnormal monthly returns follow the repurchase. Ben-Rephael, Oded, and Wohl (2013) use hand-collected data from 620 firms for 2004-2009 and also find that averaging over firm-months, acquisition prices are low, 27 basis points below the volumed weighted average price. Dittmar and Field (2015) use the most expansive period, 2004-2011, and also find that averaging over firm-months, the acquisition price of shares is low relative to the price at the end of the period and the average of the period. In contrast, I use the fraction of shares repurchased and their dollar value when forming portfolios to test for market efficiency. For their 2004-2009 sample, Ben-Raphael, Oded and Wohl (2013) also show positive abnormal returns around the earnings announcement date for repurchasing firms and abnormal returns to portfolios formed after the end of the quarter (rather than the exact month of repurchase). My data is overwhelmingly more complete and covers a longer period. I am the first to my knowledge to form calendar time portfolios based upon the actual monthly quantities of share repurchased to examine abnormal returns. And I am the first to my knowledge to examine market reactions to share repurchase surprises.

2.2 How share repurchase programs work in the U.S.

I will briefly summarize the timeline of a typical share repurchase program in the United States. First, the board of directors will authorize a share repurchase program and set certain limits to the dollar value and/or number of shares to be repurchased. Second, the firm will publicly disclose the creation of the share repurchase program so as to avoid liability under insider trading law. The disclosure will include the maximum number of shares or maximum dollar value, the objective, and how the repurchases will be made (eg. open-market repurchases). These repurchase program announcements have been examined extensively in the prior literature.

To execute the share repurchase program and comply with all SEC rules, companies typically employ the services of an investment bank or some financial firm. To avoid liability under Section 9(a) and 10(b) of the Securities Exchange Act, firms will take steps to place themselves under the Rule 10b-18 safe harbor. The rules of the safe harbor are geared toward preventing price manipulation: eg. no-trading within 10 minute of the close for most firms, no purchasing more than 25 percent of average daily trading volume, and all transactions must be at a “price that does not exceed the highest independent bid or the last independent transaction price, whichever is higher, quoted or reported in the consolidated system.” Whether or not the firm transacts under the safe harbor, the firm is required to not trade on material non-public information. Compliance with trading rules is substantial but not complete: Cook, Krigman, and Leach (2003) obtained detailed data on 54 firms’ repurchase programs and found the firms generally complied with the requirements of the safe harbor but that only two complied fully on all individual trades.

Sometimes firms will implement a 10b5-1 trading plan, essentially an auto pilot trading plan that allows a firm to continue to repurchase while in the possession of material inside information because the trading strategy was set at a time when the firm was not in the presence of material inside information. Regulation S-K (the amended rule) requires firms to disclose in their quarterly filings a table showing the number of shares purchased, the average price paid, the number of

shares purchased pursuant to a public program, and the remaining authorization. That table is my source of data (e.g. figure 2.2). The list here is by no means an exhaustive enumeration of applicable law, regulations, and rules. And there are numerous other requirements for a tender offer.

It's important to understand that the creation of a share repurchase program in no way commits a firm to repurchase a particular quantity of shares or repurchase at a particular time. Indeed, it is not uncommon for firms to announce repurchase programs and then never repurchase any shares whatsoever. The firm may also not repurchase for months, then begin repurchasing. No reporting is required until the quarterly filing. Programs will often be reauthorized before they expire and authorizations increased before the limits are reached.

In the data, there is huge heterogeneity as to the frequency and size of repurchases. While dividends are quite auto-correlated and sticky, share repurchases have huge variation.

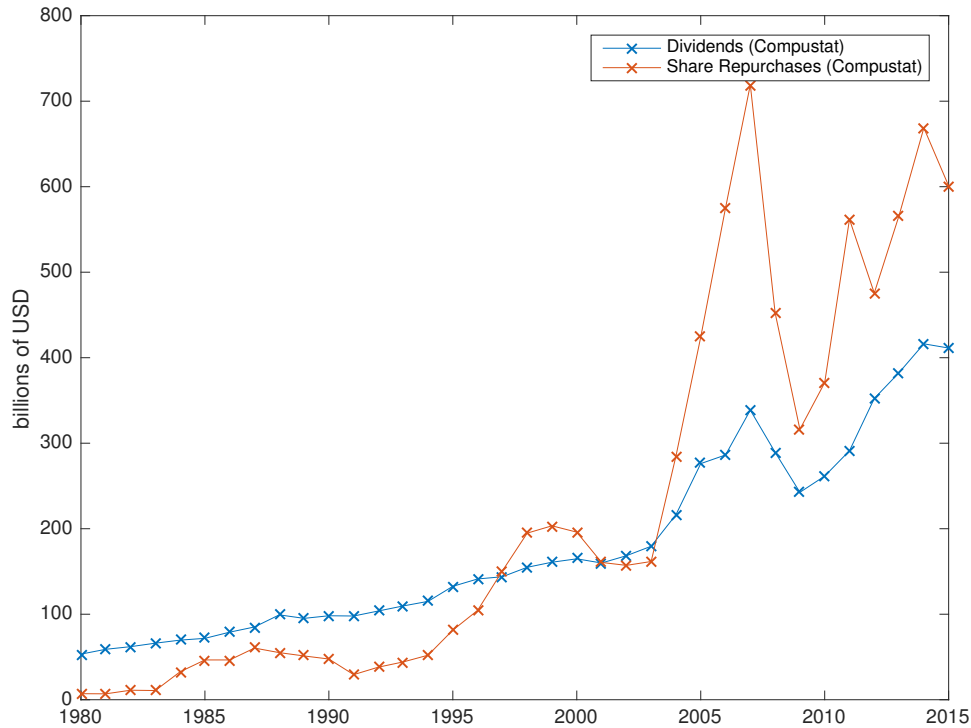


Figure 2.1: Dividends and share repurchases for publicly listed U.S. companies

This figure shows the amount spent on dividends and share repurchases by fiscal year based upon Compustat data. Dividends is DVC and share repurchases is PRSTKC.

2.3 How I obtain monthly repurchase data

The conventional sources of share repurchase data, CRSP and Compustat, give only imperfect, quarterly estimates of share repurchases and don't distinguish between shares acquired in the market and shares acquired through other means, such as shares returning to the company as part of a broader employee compensation plan. Stephens and Weisbach (1998) and Banyi et. al. (2008) discuss many of the problems.

A significant change occurred though in 2003 when the Securities and Exchange Commission amended the Rule 10b-18 safe harbor against violations of Section 9(a)(2) and 10(b) of the Securities Exchange Act and Regulation S-K's reporting requirements. Under the amended rules, the SEC would require companies to disclose monthly data on share repurchases in their 10-Q or 10-K

filings. An example of the table now available is shown in figure 2.2. There are five distinct differences with Compustat and CRSP sources: (1) you clearly observe the acquisition price, (2) you clearly observe the number of shares, (3) you observe how many shares were acquired pursuant to a repurchase program, (4) you observe the data on a monthly basis, and (5) observe who has a publicly announced, board authorized share repurchase program. I automatically parse nearly all 10-Q and 10-K filed from mid 2004 through 2015 to extract extensive, monthly data on share repurchases.

Period	Total Number of Shares Purchased	Average Price Paid per Share	Total Number of Shares Purchased as Part of Publicly Announced Plans or Programs	Approximate Dollar Value of Shares that May Yet be Purchased under the Plans or Programs
				(in millions)
April 1, 2013 – April 30, 2013	0	\$ 0.00	0	\$ 4,614
May 1, 2013 – May 31, 2013	7,002,462	\$ 32.61	7,002,462	\$ 4,386
June 1, 2013 – June 30, 2013	23,632,259	\$ 32.65	23,632,259	\$ 3,614
	30,634,721		30,634,721	

Figure 2.2: Excerpt from a Microsoft 10-K

This excerpt from a Microsoft 10-K is an example of the type of table from which my parsing software extracts monthly data on repurchases within the most recent quarter. 10-Qs also contain this table. The content of this table is based upon the requirements of SEC regulation. Compared to conventional data sources, the data is by month, shows the number of shares repurchased in a public program, shows the average price paid, and shows who has outstanding programs.

Figure 2.2 shows an example of the table I parse in a 10-K. In this example, Microsoft repurchased 7 million shares in the period of May 1, 2013 to May 31, 2013 and 23.6 million shares in June. Another notable feature of this data is that you have a more complete record of who has publicly announced share repurchase programs than is recorded in the ThomsonOne Mergers and Acquisitions database, a traditional source for program announcements. I link increases in share repurchase authorizations as implied by authorized totals in the 10-Q and 10-K filings with self acquisition announcements recorded in ThomsonOne Mergers and Acquisitions database and find that far from all share repurchase authorizations make it to the database.

To obtain the monthly 10-Q, 10-K share repurchase data in a usable form, I downloaded more

than a terabyte of 10-Q and 10-K filings for 2004-2015 to Amazon Web Services's S3 storage. I wrote a custom parser in Java that runs on an Amazon EC2 instance, utilizing JSoap to parse the HTML and custom code to find and extract data from the repurchase table. I extract numerous features from each HTML table within a 10-Q or 10-K filing, and if the table's feature vector occupies a certain region of the feature space, the table is declared to denote repurchases and I extract data. More details are given in the Appendix. Among publicly traded firms, the parser produces 74,863 firm-month observations with positive share repurchases pursuant to a public program from the period 2004-2015. My sample includes 3367 public firms with repurchases that are also in CRSP. Table 2.1 shows a year by year summary. The table confirms that many firms with active public programs do not repurchase any shares in a given month, and in fact, many firms with repurchase authorizations don't repurchase any shares in an entire year.



Figure 2.3: Overview of parsing system

I download approximately 1.2 terabytes of 10-Q and 10-K from SEC's Edgar database onto an Amazon S3 bucket (i.e. cloud storage). Custom java software (written by me) running in a multi-core EC2 instance iterates over the filings, parses the HTML, locates the repurchase table, and extracts the repurchase data, which is then stored in a PostgreSQL database on Amazon Relational Database Services. I extract 74,863 firm-months with positive repurchases pursuant to a public program with 3,367 firms.

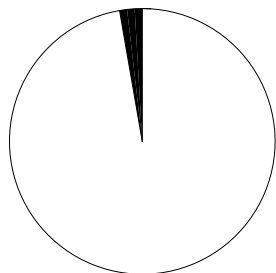
Table 2.1: Summary statistics

This table shows number of firm months with positive public program repurchases, zero repurchases pursuant to a public program, and the number of distinct firms for each. Only firms with reported public programs and whose quarterly totals are consistent with Compustat data are included. Observations are aggregated by calendar year.

Year	Firm Months		Distinct Firms	
	Positive Public	Zero Public	Firms With	Repurchasing Firms
	Program	Program	Programs	
	Repurchases	Repurchases		
2004	886	691	610	439
2005	5248	3470	1385	1052
2006	6369	4317	1613	1243
2007	7349	4889	1868	1457
2008	7115	5479	1970	1525
2009	3983	5684	1453	846
2010	5119	5913	1544	983
2011	6432	6015	1751	1209
2012	6542	6126	1728	1196
2013	6529	6207	1700	1139
2014	7151	6219	1768	1229
2015	6277	5034	1772	1247

With regards to the share acquisition price, I am looking for small effects on the order of basis points and data quality is of extreme importance. To validate the accuracy of my automated data extraction code, I aggregate my monthly observations at the quarterly level and compare with the Compustat. Figure 2.4 show a 97 percent match rate for prices (conditional on we both have non-zero and non-missing data).

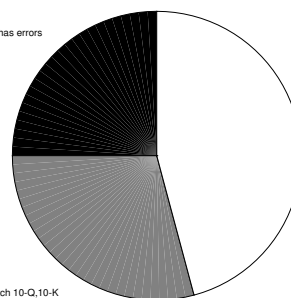
3%: My parser and Compustat disagree on average price paid in the quarter



97%: My parser and Compustat agree on average price paid in the quarter 29%: Compustat doesn't match 10-Q, 10-K

(a) Price match rate with Compustat

25%: 10-Q, 10-K has errors



46%: My parse doesn't match 10-Q, 10-K

(b) Sample of 50 firm-quarters where Compustat and I don't match.

Figure 2.4: Consistency of average price paid in the quarter with Compustat

The (a) figure shows the share of quarterly observations where the average purchase price of shares for the quarter as computed from my monthly data matches the CSHOPQ variable in Compustat. Amidst the 3 percent of non-matches, I drew a random sample of 50 observations and examined whether Compustat or I was in error. The results of that analysis are in the (b) subfigure. What generally leads to failure of my parser are unusually formatted tables, for example, if the company has dual class shares or otherwise provides some non-standard breakout. When I find an error in the 10-Q or 10-K, it's generally the case that the monthly observations don't add up to the quarterly total in the 10-Q or 10-K itself.

After entirely finishing my parsing software, I randomly selected a sample of 50 observations from the population of firm-quarters where I don't match the average price reported in Compustat (i.e. from among the 3 percent of inconsistencies). I examine these fifty cases by hand. In about half of these cases, Compustat has the correct value and my parser is wrong (this is almost always due to non-standard, company specific formatting of the table, such as when there are dual class shares). In about a quarter of these non-matches, my numbers match the table in the SEC filing and the Compustat numbers do not match what's written in the filing. And in another quarter of cases, the error seems to be within the filing itself (eg. what's reported for each of the three months in the filing don't add up to what's reported for the quarter in the filing).

Table 2.2: Consistency with Compustat

This table reports consistency with Compustat data conditional on both my parser and Compustat showing positive share repurchases for the quarter. I aggregate my data at the quarterly level and compare to the Compustat variables CSHOP and CSHOPQ. In my analysis, I restrict my sample to months where the quarterly aggregate is consistent with Compustat whenever precise share count or transaction price data is needed. A problem with directly parsing share counts is that they are often written in terms of thousands or millions of shares, and a complicated set of logic and regular expressions are required to try to detect the proper units. About half of non-matches are due to non-standard 10-Q, 10-K table formatting, for example if the firm reports multiple programs, reports multiple classes of shares, uses non-standard terminology, or does not use HTML.

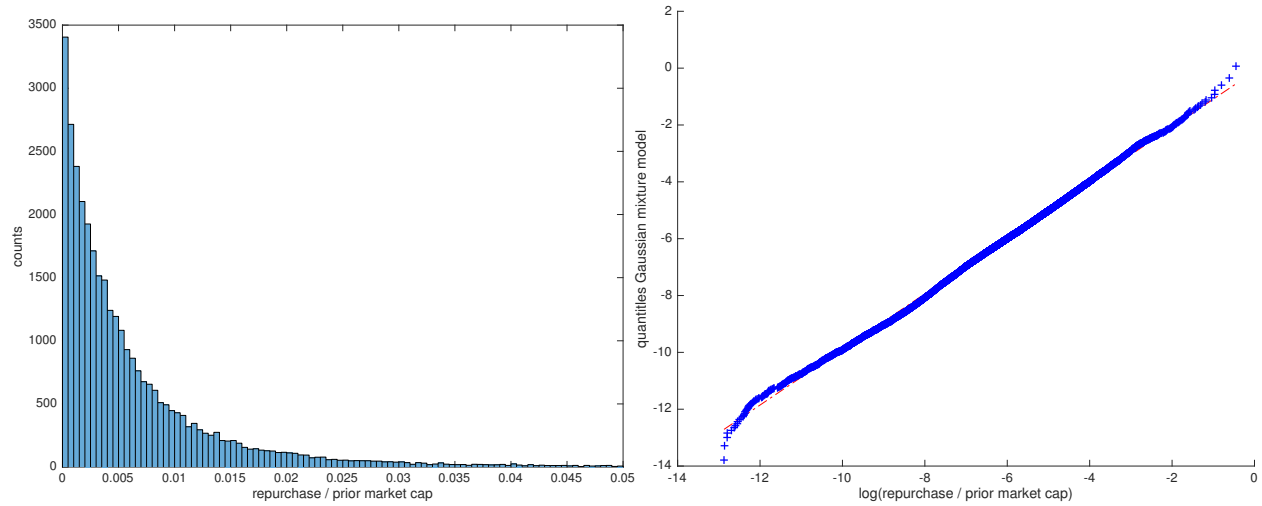
year	shares match rate	price match rate
2004	82.1	96.2
2005	83.2	97.1
2006	87.5	97.5
2007	88.8	96.1
2008	91.3	96.0
2009	94.3	96.8
2010	93.5	97.7
2011	93.3	97.5
2012	93.4	97.9
2013	93.9	97.6
2014	92.9	97.7
2015	93.0	97.7

In any case, I don't use the non-matching data. For any analysis sensitive to price or share count data, I restrict my sample to monthly observations from quarters where the quarterly aggregates match Compustat. Further details on data cleaning are in the appendix.

The standard concern with missing data is that the data you don't see is not like the data you do see, that the censoring is endogenous. This shouldn't be a serious concern here. Based upon extensive inspection by hand, common reasons for non-matching aggregates include typos in Compustat or SEC filing data, non-HTML filings, non-standard formatted tables (eg. due to dual class shares, due to especially complex transactions), or parsing errors recognizing column headers. I would argue the typo and parsing type errors lead to missing data that's quite close to missing

completely at random (MCAR). Other ways data is excluded is related to firm characteristics. For example, I exclude non-HTML filings (which tend to be micro-sized firms), but I argue this doesn't matter at a practical level.

Table 2.2 has the match rate for share counts by year. Matching the share counts is more difficult because of significant issues of processing language to determine the units used in a particular column of the repurchase table in the 10-Q or 10-K filing. I use an extensive set of regular expressions to pickup text denoting units.



(a) Histogram of share repurchases (truncated at .05) (b) Quantile-quantile plot of log repurchase fraction vs. fitted Gaussian mixture model ($k = 2$)

Figure 2.5: Distribution of share repurchases as a share of market cap

Subfigure (a) shows a histogram of the repurchase fraction (i.e. dollars spent on repurchases divided by prior market). Subfigure (b) shows a quantile-quantile plot of the empirical distribution over the log share repurchase fraction versus a mixture of two gaussian distributions fit to the data via expectation maximization. The gaussian distributions are heavily overlapping.

2.4 The distribution of repurchases

The distribution of share repurchases is given in figure 2.5(a). The most important takeaway is that the vast majority of firm-months with positive repurchases have extremely small repurchases relative to market cap. The skewness is huge. Figure 2.5(b) shows a quantile-quantile plot of

the empirical distribution versus a fitted lognormal gaussian mixture model. The nice 45 degree line shows that the distribution of share repurchase fraction (conditional on being positive) can be well approximated by a mixture of two heavily overlapping lognormal distributions. This is fit via expectation maximization, the standard iterative optimization method to fit Gaussian mixture models. Figure 2.7 shows that incidence of share repurchases is linearly increasing in log firm size. About half of large cap firms repurchase shares pursuant to a public program. Few small firms do. Figure 2.6 shows what share for firm-quarters have positive repurchases by firm industry.

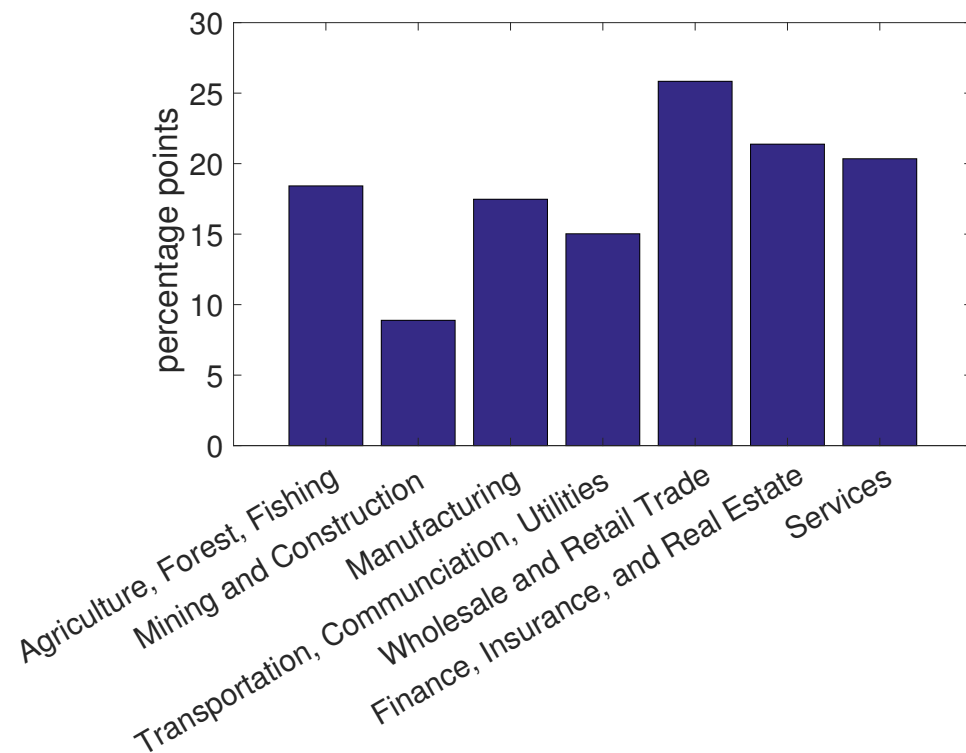


Figure 2.6: Share of firm quarters with positive repurchases by firm industry

This figure shows the fraction of firm-quarters with positive share repurchases by industry (i.e. 1 digit SIC code).

Stock price and return data comes from CRSP, accounting data from Compustat, Fama-French factor data from Ken French's website, and earnings data is from IBES. The SEC filing date for 10-Qs and 10-Ks comes from the WRDS SEC analytics suite.

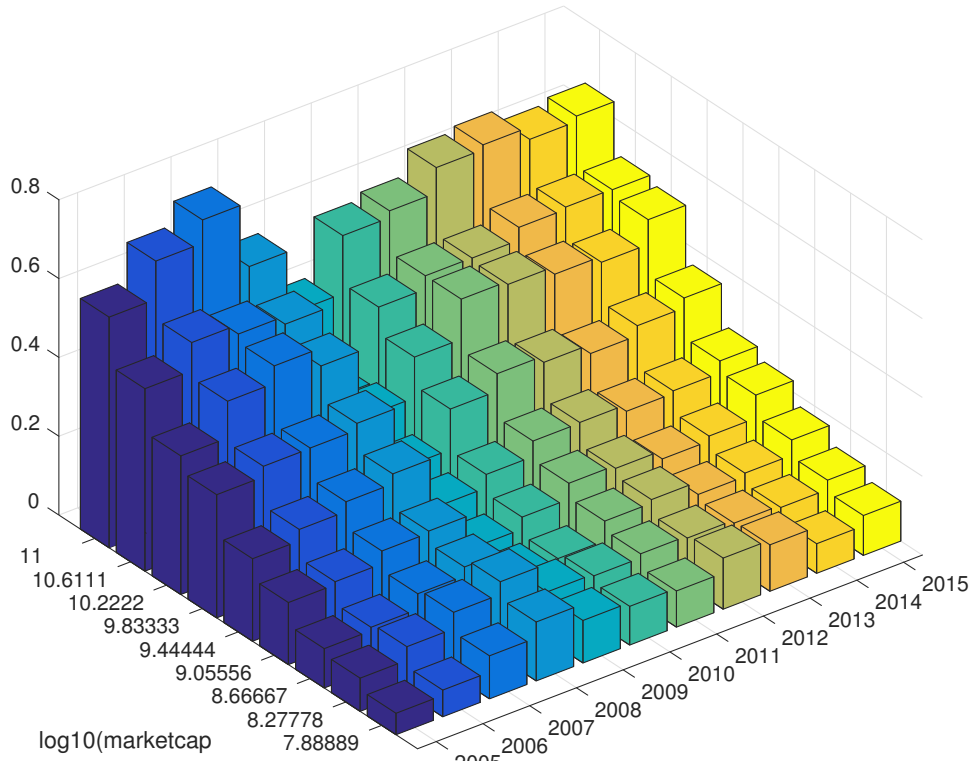


Figure 2.7: Fraction of firm-quarters with positive repurchases pursuant to a public program

This figure shows the fraction of firm-quarters in a year with positive public program share repurchases by year and $\log_{10}(\text{marketcap})$. Eg. 9 denotes $10^9 = 1$ billion dollar firm and 11 denotes a $10^{11} = 100$ billion dollar firm. Firm-size explains a huge amount of the cross-sectional variation in who repurchases shares.

Chapter 3

Do firms earn abnormal returns on actual repurchases?

To examine whether repurchasing firms achieve positive abnormal returns, I form calendar time portfolios monthly based upon prior repurchase activity and compute Jensen's alpha of portfolio returns relative to various asset pricing models. These will be joint tests of the asset pricing model and strong form market efficiency since share repurchases are not required to be disclosed in the United States until the quarterly filing. The calendar time portfolio approach naturally produces consistent test-statistics in the presence of cross-sectional correlation of returns. As discussed in Fama (1998) and Mitchell and Stafford (2000), the buy-and-hold abnormal return (BHAR) approach can overstate test-statistics.

I define the repurchase fraction as the fraction of prior market cap repurchased by a firm in a month. I will consider four different types of weightings for firms in a portfolio: repurchase fraction, repurchase dollar value, equal weighting and firm value weighting. Observations where more than 5 percent of market cap is repurchased are excluded because these generally indicate tender offers or other types of large, special transactions that aren't open-market share repurchases. The portfolio return series runs from 2005 to 2015. The predominant model of expected returns

I will use is the Fama French five factor model (Fama French 2015) as it includes an operating profitability factor.

3.1 Portfolios formed with one to seven month holding periods

If firm i repurchases shares in month t , firm i will enter a share repurchase portfolio in month $t + 1$. In this first series of portfolios, the holding period for the shares will vary from 1 to 7 months depending on the portfolio. Figure 3.1 and 3.2 reports alphas relative to the Fama-French three factor and five factor model respectively.

We can immediately see that the portfolios with higher weights on smaller firms achieve statistically significant alphas over a broad set of holding periods while the value and dollar weight portfolios do not. Perhaps suggestive, abnormal returns are highest in the repurchase fraction weighted portfolio at the two to three month time frame. In unreported results, I also test short-term reversal and momentum factors and they do not substantively alter the picture..

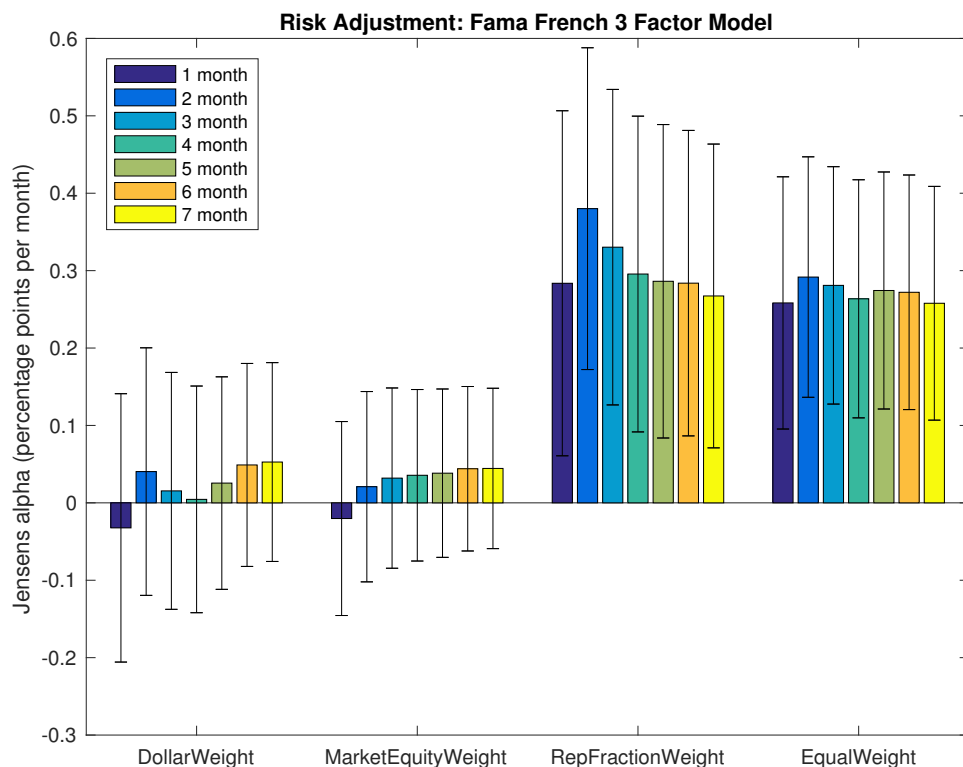


Figure 3.1: Abnormal returns to share repurchases (relative to Fama-French three factor model)

This figure shows monthly abnormal returns, measured by Jensen's alpha, for 28 portfolios formed on share repurchases. Portfolio composition changes monthly. A firm's shares enter the portfolio in month t if the firm repurchased shares in month $t - 1$. Different portfolios are formed where the holding period is 1, 2, 3, 4, 5, 6, or 7 months. Four different portfolio weights are applied: weight all repurchasing firms equally, weight firms by dollar value of share repurchases, weight firms by the fraction of prior market cap repurchased, and weight firms by their market capitalization. Dollar weighting or market equity weighting will be dominated by large firms while the other two weightings are dominated by smaller firms. Abnormal returns are measured relative to the Fama-French three factor model. Transactions more than 5 percent of market cap are excluded as these overwhelmingly are tender offers or other corporate transactions that aren't open-market share repurchases. Error bars show the 95 percent confidence interval calculated using heteroskedastic robust standard errors.

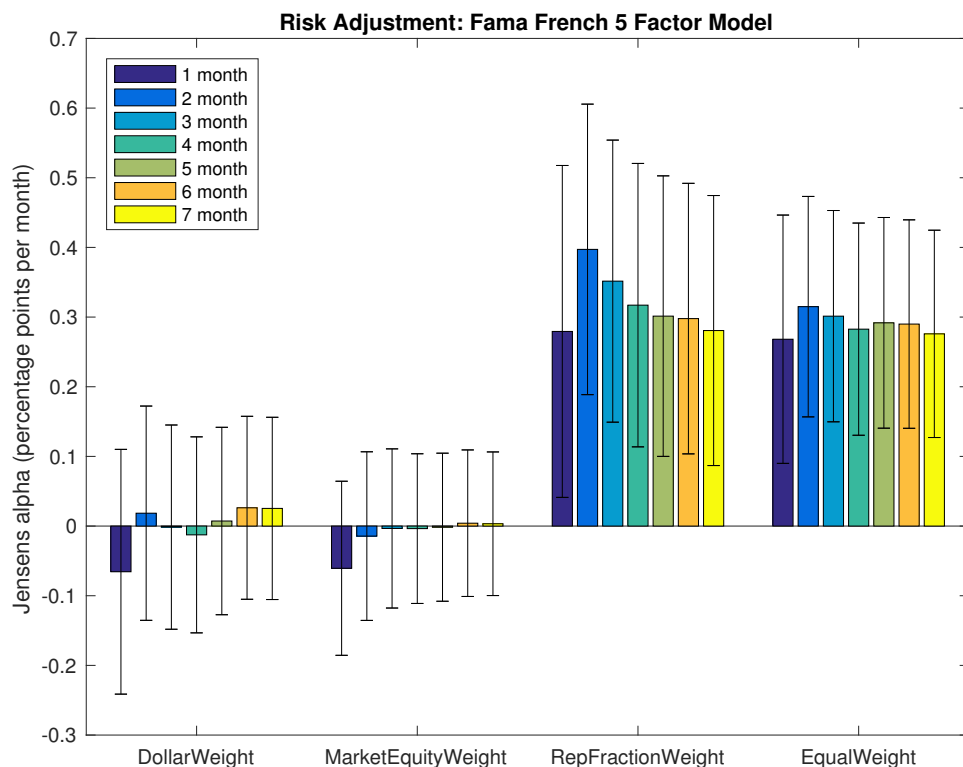


Figure 3.2: Abnormal returns to share repurchases (relative to Fama-French five factor model)

This figure shows monthly abnormal returns, measured by Jensen's alpha, for 28 portfolios formed on share repurchases. Portfolio composition changes monthly. A firm's shares enter the portfolio in month t if the firm repurchased shares in month $t - 1$. Different portfolios are formed where the holding period is 1, 2, 3, 4, 5, 6, or 7 months. Four different portfolio weights are applied: weight all repurchasing firms equally, weight firms by dollar value of share repurchases, weight firms by the fraction of prior market cap repurchased, and weight firms by their market capitalization. Dollar weighting or market equity weighting will be dominated by large firms while the other two weightings are dominated by smaller firms. Abnormal returns are measured relative to the Fama-French five factor model. Transactions more than 5 percent of market cap are excluded as these overwhelmingly are tender offers or other corporate transactions that aren't open-market share repurchases. Error bars show the 95 percent confidence interval calculated using heteroskedastic robust standard errors.

3.2 Portfolios based upon NYSE market equity quintiles

The second series of portfolios separate firms by NYSE market equity quintiles and have a three month holding period. Table 3.1 reports the alphas. Estimated alpha for all portfolios of firms in the top market equity quintile are near zero (i.e. the largest of firms). On the other hand, the estimated alpha for the repurchase fraction weighted portfolio in the fourth quantile of size is

statistically significant and about 4 percent per year. The abnormal returns is not simply a small firm phenomenon. Many other portfolios are near the edge of significance. For estimating alphas, eleven years is a fairly short time frame, and the 95 percent confident interval for estimated alphas is rather large. The last row computes returns relative to the S&P500 index, and these are nearly all significant. This is notable because realistically, the S&P500 may be the benchmark firm managers have in mind rather than five factor model Jensen's alpha.

Table 3.1: Alphas of three month repurchase portfolios by NYSE market cap quintile

This table shows estimated alpha for five portfolios based upon NYSE market capitalization breakpoints. Within each portfolio, firms are weighted based on the fraction of prior market cap they repurchased. Portfolios are rebalanced monthly. A firm enters the portfolio in month t and held for three months if the firm repurchased shares in month $t - 1$. The Size1 portfolio has firms in the bottom quintile of firm size. Abnormal returns are measured relative to the Fama-French three factor, five factor model, and the five factor model plus a short-term reversal factor. The final line simply compares returns to the S&P500 index. Repurchases more than 5 percent of market cap are excluded as these overwhelmingly are tender offers or other corporate transactions that aren't open-market share repurchases. Standard errors are in parenthesis. One, two, and three stars denote significance at the 5%, 1%, and .1% level respectively.

	Repurchase Fraction Weighted					Repurchase Dollar Value Weighted				
	Size1	Size2	Size3	Size4	Size5	Size1	Size2	Size3	Size4	Size5
3 Factor	0.40**	0.53**	0.23	0.32*	0.07	0.29	0.55**	0.17	0.30	-0.04
Alpha	(0.15)	(0.17)	(0.14)	(0.16)	(0.10)	(0.16)	(0.16)	(0.14)	(0.15)	(0.09)
5 Factor	0.46**	0.51**	0.21	0.36*	0.10	0.32	0.52**	0.16	0.33*	-0.06
Alpha	(0.15)	(0.17)	(0.14)	(0.15)	(0.11)	(0.16)	(0.16)	(0.14)	(0.14)	(0.08)
5 Factor + StRev	0.46**	0.52**	0.22	0.37**	0.11	0.31	0.52**	0.17	0.34*	-0.05
Alpha	(0.15)	(0.16)	(0.13)	(0.14)	(0.09)	(0.16)	(0.16)	(0.13)	(0.14)	(0.08)
5 Factor + Mom	0.49***	0.54***	0.23	0.36*	0.11	0.33*	0.55***	0.16	0.34*	-0.07
Alpha	(0.13)	(0.16)	(0.14)	(0.15)	(0.10)	(0.16)	(0.16)	(0.14)	(0.14)	(0.09)
Ret - RetSP500	0.53*	0.77**	0.49*	0.58**	0.27**	0.44	0.78***	0.41*	0.54**	0.12
	(0.21)	(0.23)	(0.20)	(0.18)	(0.10)	(0.23)	(0.23)	(0.19)	(0.17)	(0.10)

3.3 Portfolios formed on repurchase quantile for firms with repurchase programs

Table 3.2 shows estimated alphas and betas for portfolio returns constructed on quantile of repurchase activity with a three month holding period. For robustness, I exclude firms in the bottom quintile of NYSE market capitalization and limit the influence of tiny firms. No clear pattern emerges for the value weight portfolio, but in the equal weight portfolio, the higher high repurchase activity portfolios have significant, positive returns. Furthermore, the estimated alphas increase monotonically: going from the no repurchase portfolio to the 1st quartile of activity portfolio all the way to the 4th quartile of activity portfolio.

The equal weight, long-short portfolio of going long high repurchase activity and short zero repurchase activity has an estimated alpha of 29 basis points per month or approximately 3.5 percent per year.

Table 3.2: Portfolios by quantile of repurchase activity

This table shows estimated alphas and betas for calendar time portfolios formed on quantile of repurchase activity in a month among firms with outstanding public market repurchase authorizations as reported in 10-Qs and 10-Ks. A firm enters a portfolio k in month t if the fraction of outstanding shares repurchased in month $t - 1$ falls in the k th quantile of activity conditional among repurchasers. The zero portfolio is comprised of firms (with active programs) that did not repurchase. Firms stay in the portfolio for three months. Repurchases larger than 5 percent of market cap are excluded as these overwhelmingly are tender offers or transactions other than open market repurchases. Firms in the bottom quintile of size by NYSE market cap are also excluded to limit influence of tiny firms. The sample runs from 2005 through 2015. The Q4-Zero portfolio goes long the Q4 portfolio and short the Zero portfolio. Standard errors are in parenthesis. One, two, and three stars denote significance at the 5%, 1%, and .1% level respectively.

Panel A: Fama French three factor model

	Value Weighted						Equal Weighted					
	Zero	Q1	Q2	Q3	Q4	Q4-Zero	Zero	Q1	Q2	Q3	Q4	Q4-Zero
alpha	-0.04 (0.08)	-0.07 (0.11)	0.12 (0.08)	0.11 (0.10)	-0.08 (0.11)	-0.03 (0.14)	-0.03 (0.08)	0.15 (0.09)	0.20* (0.08)	0.20* (0.09)	0.27* (0.11)	0.29** (0.10)
rmrf	1.04*** (0.03)	1.01*** (0.03)	0.91*** (0.03)	0.97*** (0.03)	0.96*** (0.03)	-0.08 (0.04)	1.09*** (0.02)	0.97*** (0.03)	0.99*** (0.03)	1.02*** (0.04)	1.00*** (0.04)	-0.09* (0.04)
smb	0.05 (0.03)	-0.08 (0.06)	-0.04 (0.04)	-0.15* (0.06)	0.01 (0.06)	-0.04 (0.07)	0.52*** (0.05)	0.45*** (0.04)	0.36*** (0.03)	0.33*** (0.04)	0.40*** (0.04)	-0.12** (0.04)
hml	-0.01 (0.05)	0.06 (0.05)	-0.06 (0.04)	-0.10* (0.04)	-0.12* (0.05)	-0.11 (0.07)	0.19*** (0.04)	0.09* (0.04)	-0.05 (0.03)	-0.06 (0.04)	-0.02 (0.05)	-0.21*** (0.04)
N	132	132	132	132	132	132	132	132	132	132	132	132
r2	0.97	0.93	0.95	0.92	0.91	0.12	0.98	0.96	0.97	0.96	0.95	0.46

Panel B: Fama French five factor model

	Value Weighted						Equal Weighted					
	Zero	Q1	Q2	Q3	Q4	Q4-Zero	Zero	Q1	Q2	Q3	Q4	Q4-Zero
alpha	-0.02 (0.08)	-0.14 (0.10)	0.11 (0.09)	0.02 (0.09)	-0.07 (0.11)	-0.04 (0.14)	-0.04 (0.07)	0.14 (0.08)	0.20* (0.08)	0.17 (0.09)	0.27* (0.11)	0.31** (0.10)
rmrf	1.03*** (0.03)	1.05*** (0.03)	0.92*** (0.03)	1.01*** (0.03)	0.96*** (0.04)	-0.08 (0.05)	1.09*** (0.03)	0.97*** (0.03)	0.99*** (0.03)	1.03*** (0.04)	1.00*** (0.04)	-0.09* (0.04)
smb	0.04 (0.03)	-0.05 (0.05)	-0.04 (0.04)	-0.11 (0.06)	-0.00 (0.07)	-0.04 (0.08)	0.52*** (0.06)	0.45*** (0.05)	0.36*** (0.04)	0.34*** (0.04)	0.39*** (0.05)	-0.13** (0.05)
hml	-0.02 (0.05)	0.01 (0.05)	-0.07 (0.04)	-0.10 (0.05)	-0.17* (0.07)	-0.15 (0.09)	0.22*** (0.05)	0.09* (0.04)	-0.03 (0.03)	-0.03 (0.04)	-0.01 (0.06)	-0.23*** (0.05)
cma	0.03 (0.06)	0.20* (0.09)	0.04 (0.07)	0.02 (0.08)	0.17 (0.12)	0.14 (0.15)	-0.10 (0.06)	-0.01 (0.07)	-0.06 (0.07)	-0.09 (0.09)	-0.05 (0.11)	0.05 (0.10)
rmw	-0.06 (0.05)	0.15 (0.10)	0.02 (0.07)	0.26** (0.09)	-0.08 (0.10)	-0.01 (0.12)	0.06 (0.08)	0.04 (0.08)	0.01 (0.06)	0.11 (0.06)	-0.01 (0.08)	-0.07 (0.07)
N	132	132	132	132	132	132	132	132	132	132	132	132
r2	0.97	0.93	0.95	0.93	0.91	0.13	0.98	0.96	0.97	0.96	0.95	0.46

A consistent pattern emerges that firms in the top quintile of NYSE market capitalization do not appear to earn positive abnormal returns on their share repurchases but that other firms do.

3.4 Portfolios formed at quarter end on Compustat data

For completeness, I also form portfolios at the end of a quarter on Compustat share repurchase data (rather than my special monthly data). This allows a much longer sample from 1985-2015. Table 3.3 shows the results. Panel A represents a joint test of asset pricing models and strong form market efficiency because share repurchase data may not yet be disclosed at the end of the quarter. Panel B is a joint test of asset pricing models and semi-strong form efficiency since after six months, the data would be publicly available from the quarterly filings. The holding period is six months.

Estimated alphas are larger for portfolios formed on non-public information (i.e. Panel A), and estimated alphas are smaller under the Fama French five factor model due to loading on the operating profitability factor.

Table 3.3: After quarter end repurchase portfolios 1985 - 2015

This table shows estimated alphas and betas for calendar time portfolios formed based on repurchase activity as reported on statement of cash flows and recorded in the Compustat variable PRSTKC. In Panel A, a firm enters the portfolio in month t if the quarter ending at $t - 1$ reports repurchases and held for six months. Since reporting repurchases is not required until quarterly SEC 10-Q or 10-K, this information may not be publicly available at the time of portfolio information. Trivial repurchase activity less than 0.1 percent of market cap or mega activity greater than 10 percent are excluded. Four different portfolio weightings are used: RepFracW weights by the repurchase fraction, RepDollarW weights by the dollar value of repurchases, EqualW equal weights, and ValueW weights by market capitalization. In Panel B, information is lagged six months so portfolios are formed on information that would be publicly available. Standard errors are in parenthesis. One, two, and three stars denote significance at the 5%, 1%, and .1% level respectively.

Panel A: Portfolios formed at the end of the quarter

	FF3				FF5				FF5+mom			
	RepFracW	RepDollarW	EqualW	ValueW	RepFracW	RepDollarW	EqualW	ValueW	RepFracW	RepDollarW	EqualW	ValueW
alpha	0.32*** (0.08)	0.24*** (0.06)	0.23*** (0.07)	0.17*** (0.05)	0.18* (0.08)	0.13* (0.07)	0.11 (0.07)	0.07 (0.04)	0.26*** (0.06)	0.19** (0.06)	0.18*** (0.05)	0.10* (0.04)
rmrf	0.98*** (0.02)	0.97*** (0.02)	0.99*** (0.02)	0.94*** (0.01)	1.03*** (0.02)	1.01*** (0.02)	1.03*** (0.02)	0.98*** (0.01)	1.01*** (0.02)	1.00*** (0.02)	1.01*** (0.02)	0.98*** (0.01)
smb	0.35*** (0.05)	-0.13*** (0.03)	0.31*** (0.05)	-0.17*** (0.02)	0.44*** (0.03)	-0.07** (0.03)	0.40*** (0.03)	-0.12*** (0.02)	0.46*** (0.03)	-0.06* (0.03)	0.42*** (0.03)	-0.12*** (0.02)
hml	0.25*** (0.05)	0.08* (0.03)	0.23*** (0.05)	0.03 (0.03)	0.16*** (0.04)	0.00 (0.03)	0.16*** (0.04)	-0.06* (0.02)	0.06 (0.03)	-0.07* (0.03)	0.07* (0.03)	-0.09*** (0.02)
cma					0.05 (0.07)	0.08 (0.06)	0.03 (0.06)	0.13** (0.04)	0.13** (0.05)	0.15** (0.05)	0.11* (0.04)	0.16*** (0.04)
rmw					0.30*** (0.05)	0.19*** (0.04)	0.28*** (0.04)	0.16*** (0.03)	0.35*** (0.04)	0.23*** (0.03)	0.32*** (0.03)	0.18*** (0.03)
mom									-0.15*** (0.02)	-0.11*** (0.03)	-0.14*** (0.02)	-0.05** (0.02)
N	372	372	372	372	372	372	372	372	372	372	372	372
r2	0.92	0.93	0.93	0.96	0.93	0.94	0.95	0.97	0.95	0.95	0.96	0.97

Panel B: Form portfolios starting six months after end of quarter

	FF3				FF5				FF5+mom			
	RepFracW	RepDollarW	EqualW	ValueW	RepFracW	RepDollarW	EqualW	ValueW	RepFracW	RepDollarW	EqualW	ValueW
alpha	0.25*** (0.07)	0.12 (0.06)	0.17** (0.07)	0.12** (0.04)	0.09 (0.06)	-0.01 (0.06)	0.02 (0.06)	0.01 (0.04)	0.16** (0.06)	0.06 (0.06)	0.09 (0.05)	0.03 (0.04)
rmrf	0.99*** (0.02)	1.00*** (0.02)	1.00*** (0.02)	0.96*** (0.01)	1.05*** (0.02)	1.04*** (0.02)	1.05*** (0.02)	1.00*** (0.01)	1.03*** (0.02)	1.03*** (0.02)	1.03*** (0.02)	1.00*** (0.01)
smb	0.36*** (0.05)	-0.12*** (0.03)	0.33*** (0.05)	-0.16*** (0.02)	0.45*** (0.03)	-0.07** (0.03)	0.42*** (0.03)	-0.12*** (0.02)	0.47*** (0.02)	-0.05* (0.02)	0.44*** (0.02)	-0.12*** (0.02)
hml	0.29*** (0.05)	0.15*** (0.03)	0.27*** (0.04)	0.06* (0.03)	0.19*** (0.04)	0.05 (0.03)	0.18*** (0.03)	-0.05 (0.02)	0.11*** (0.03)	-0.03 (0.03)	0.10*** (0.03)	-0.07** (0.03)
cma					0.08 (0.05)	0.15** (0.05)	0.08 (0.05)	0.18*** (0.03)	0.15** (0.05)	0.21*** (0.04)	0.15*** (0.04)	0.19*** (0.04)
rmw					0.32*** (0.04)	0.20*** (0.04)	0.30*** (0.04)	0.15*** (0.03)	0.36*** (0.03)	0.24*** (0.03)	0.34*** (0.03)	0.16*** (0.03)
mom									-0.12*** (0.01)	-0.12*** (0.01)	-0.12*** (0.01)	-0.03* (0.01)
N	372	372	372	372	372	372	372	372	372	372	372	372
r2	0.93	0.93	0.94	0.96	0.95	0.94	0.96	0.97	0.96	0.96	0.97	0.97

Chapter 4

When do abnormal returns occur in the quarter?

To more carefully explore when abnormal returns occur, I examine whether firms repurchasing shares have higher abnormal returns than firms not repurchasing shares over the 90 days that follow a month in which a firm repurchased. Furthermore, I will distinguish between three types of days: (i) days near earnings announcements (ii) days near the filing of a 10-Q or 10-K on EDGAR (the SEC's Electronic Data Gathering, Analysis, and Retrieval system), and (iii) days that are neither (i) nor (ii). The EDGAR filing date comes from Wharton Research Data Services SEC Analytics Suite.

4.1 Computing abnormal returns

I compute abnormal returns using several different models of expected returns. Let R_{it} be the return of firm i on day t . The abnormal return $AR_{it} = R_{it} - E[R_{it} | \mathcal{F}]$ is the return relative to some expectation of what the return is expected to be based upon risk loadings or firm characteristics.

The main specification I use for expected returns is the Fama-French five factor model (Fama

French 2015) which add operating profitability and investment factors to the classic three factor model. For robustness, I also consider several characteristic adjusted returns where a firm is matched to a portfolio return based upon firm characteristics.

$$E[R_{it} | \mathcal{F}_t] = \beta_i^{RMRF} RMRF_t + \beta_i^{SMB} SMB_t + \beta_i^{HML} HML_t + \beta_i^{CMA} CMA_t + \beta_i^{RMW} RMW_t$$

For each stock in CRSP, I compute abnormal returns that are either risk adjusted or characteristic adjusted. For each stock in CRSP, I estimate betas using monthly data and a rolling window from 30 months to 6 months prior to the date in question. These betas and the associated factor returns are then applied to the daily CRSP return data to obtain daily abnormal returns. For characteristic adjusted returns, I compute firm characteristics based upon the previously filed 10-K and match the firm with a Fama-French portfolio with similar characteristics. The regression based models are the market model, the Fama-French three factor model, and the Fama-French five factor model. The three characteristic adjusted return models will be based upon matching firms to portfolios constructed on (i) size and book to market ratio, (ii) operating profitability and book to market ratio, and (iii) size and operating profitability.

4.2 The timing of abnormal returns

Using my data parsed from 10-Q and 10-K filings, I restrict the sample to firms with positive outstanding share repurchase authorizations. This can be interpreted as an initial round of pruning/matching so that the control group is similar to repurchasing firms in that they both have repurchase programs. I then construct various indicator variables to distinguish firm days. Indicator $Repurchase90Days_{it}$ takes the value 1 if in the 90 days prior to t includes the end of a month in which firm i repurchased shares. Indicator $NearEarningsDate_{it}$ is 1 if t is an earnings announcement day for firm i or up to five trading days after. Indicator $NearFilingDate_{it}$ is the same except for the filing date of 10-Q or 10-K on EDGAR as reported in the WRDS Sec Analytics Suite.

I then run panel regressions of abnormal returns on various indicators, for example:

$$AR_{it} = \beta_0 + \beta_1 Repurchase90Days_{it} + \beta_2 NearEarningsDate_{it} + \beta_3 NearFilingDate_{it} + \beta_4 NearEarningsDate_{it} Repurchase90Days_{it} + \beta_5 NearFilingDate_{it} Repurchase90Days_{it} + \epsilon_{it}$$

Table 4.1 shows the results using six different models of expected returns for robustness. The robust result is that repurchasing firms earn significant, positive abnormal returns near the filing date, the first availability of the 10-Q and 10-K on the EDGAR system. The finding is significant and robust across many specifications for the cross-section of abnormal returns. In short windows like this (i.e. six trading days), estimates of abnormal returns will be less sensitive to different specifications for the cross-sectional of expected returns.

Table 4.1: Share repurchases and timing of abnormal returns: different models of expected returns

This table shows the result of regressing daily abnormal returns on various indicators. *RepurchaseLast90Days_{it}* takes the value 1 if the 90 days prior to t overlaps a month in which firm i repurchased shares. *NearEarningsDate_{it}* takes the value 1 on an earnings announcement date and any of the following five days of trading. *NearFilingDate_{it}* does the same but for the first availability of a quarterly filing on the SEC's EDGAR system. All coefficients have units of basis points (i.e. hundredths of a percentage point) per day. Risk adjusted returns are calculated based upon the market model (MM), Fama-French three factor model (FF3), and Fama-French 5 factor model (FF5). Characteristic adjusted returns match on size and book to market ratio, book to market ratio and operating profitability, and size and operating profitability respectively. The sample covers 2005 through 2015 and includes only firms with publicly announced repurchase programs. Standard errors are clustered by date because of cross-sectional correlation. Standard errors are in parenthesis. One, two, and three stars denote significance at the 5%, 1%, and .1% level respectively.

Panel A: Full sample						
	Risk Adjusted			Characteristic Adjusted		
	(1) MM	(2) FF3	(3) FF5	(4) Size BM	(5) Size OP	(6) BM OP
RepurchaseLast90Days	-0.01 (0.73)	0.50 (0.47)	0.60 (0.55)	0.49 (0.63)	0.37 (0.58)	0.46 (0.57)
NearEarningsDate	3.45 (1.92)	5.10** (1.73)	5.81** (1.79)	3.32* (1.61)	3.00 (1.60)	1.36 (1.73)
NearFilingDate	-1.96 (2.36)	-1.92 (1.65)	-3.06 (1.74)	-0.22 (1.68)	-0.65 (1.68)	-0.35 (1.95)
RepurchaseLast90Days × NearEarningsDate	1.03 (1.89)	0.63 (1.80)	0.24 (1.84)	2.05 (1.79)	2.15 (1.74)	2.46 (1.73)
RepurchaseLast90Days × NearFilingDate	5.20* (2.09)	5.50** (1.72)	6.64*** (1.80)	4.78** (1.85)	4.72** (1.80)	4.27* (1.76)
Observations	3254385	3254385	3254385	3400400	3400400	3397661
Clusters	2897	2897	2897	2897	2897	2897

Panel B: Financial crisis Jan 2008 to July 2009						
	Risk Adjusted			Characteristic Adjusted		
	(1) MM	(2) FF3	(3) FF5	(4) Size BM	(5) Size OP	(6) BM OP
RepurchaseLast90Days	-1.20 (3.62)	-0.00 (1.98)	0.48 (2.40)	0.44 (3.18)	0.05 (2.91)	-0.21 (2.70)
NearEarningsDate	10.60 (7.90)	13.08* (6.54)	13.81* (6.69)	7.33 (6.27)	7.21 (6.28)	4.42 (7.10)
NearFilingDate	-12.06 (10.32)	-6.53 (6.72)	-8.28 (6.99)	-6.55 (6.88)	-7.74 (6.95)	-4.81 (7.86)
RepurchaseLast90Days × NearEarningsDate	0.55 (7.76)	1.55 (6.76)	2.81 (6.71)	1.95 (7.18)	1.91 (6.95)	2.92 (6.70)
RepurchaseLast90Days × NearFilingDate	10.51 (9.16)	7.29 (6.98)	10.13 (7.10)	9.43 (7.77)	9.55 (7.51)	10.61 (7.13)
Observations	525709	525709	525709	560216	560216	559651
Clusters	399	399	399	399	399	399

To my knowledge, this is the first documentation of market reaction to share repurchases on 10-Q, 10-K filing dates. Ben-Raphael et. al. (2013) found that the repurchase fraction is associated with abnormal returns around earnings announcement dates, but they did not examine the filing date. Share repurchases during the quarter are sometimes disclosed on earnings calls or the release of preliminary financials, but they definitely become publicly available with the filing of the 10-Q or 10-K. For about a third of firms, the 10-Q, 10-K filing date is the same as the earnings announcement date as recorded in Compustat.

Note also that the positive coefficient $NearEarningsDate_{it}$ is consistent with the earnings announcement premium of Frazzini and Lamont (2007) and Barber et. al. (2013): unconditional on earnings news, firms earn positive abnormal returns around earnings announcements. The negative coefficient on $NearFilingDate_{it}$ is the other side of the coin to a positive coefficient on $NearFilingDate_{it}Repurchase90Days_{it}$; since there isn't an unconditional filing date effect, one being positive would imply the other is negative.

Table 4.2 explores a more nuanced breakdown of timing, distinguishing between more recent and more distant repurchases.

Table 4.2: Share repurchases and timing abnormal returns

Let AR_{it} denote the daily abnormal return of firm i on date t based on the Fama-French five factor model. Abnormal returns are based on monthly betas estimated from a rolling window 30 months to 6 months to date t . This table shows estimates of a panel regression of AR_{it} on various indicator variables. *RepurchaseLast90Days_{it}* takes the value 1 if the 90 days prior to t overlaps a month in which firm i repurchased shares. *NearEarningsDate_{it}* takes the value 1 on an earnings announcement date and any of the following five days of trading. *NearFilingDate_{it}* does the same but for the first availability of a quarterly filing on the SEC's EDGAR system. All coefficients have units of daily abnormal returns, reported in basis points (i.e. hundredths of a percentage point). The sample covers 2005 through 2015 and includes only firms with publicly announced repurchase programs. Standard errors are clustered by date because of cross-sectional correlation. Standard errors are in parenthesis. One, two, and three stars denote significance at the 5%, 1%, and .1% level respectively.

	(1) FF5	(2) FF5	(3) FF5	(4) FF5
<i>Share Repurchase Indicators:</i>				
RepurchaseLast90Days	1.16* (0.53)		0.60 (0.55)	
RepurchaseLast30Days		0.90 (0.56)		0.55 (0.58)
RepurchaseLast31-90Days		2.25*** (0.67)		0.83 (0.69)
<i>Information Day Indicators:</i>				
NearEarningsDate			5.81** (1.79)	5.81** (1.79)
NearFilingDate			-3.06 (1.74)	-3.06 (1.74)
<i>Interactions</i>				
RepurchaseLast90Days × NearEarningsDate			0.24 (1.84)	
RepurchaseLast90Days × NearFilingDate			6.64*** (1.80)	
RepurchaseLast30Days × NearEarningsDate				-2.51 (1.91)
RepurchaseLast30Days × NearFilingDate				7.43*** (1.87)
RepurchaseLast31-90Days × NearEarningsDate				10.63*** (2.70)
RepurchaseLast31-90Days × NearFilingDate				3.19 (2.53)
Observations	3254385	3254385	3254385	3254385
Clusters	2897	2897	2897	2897

4.3 The timing of abnormal returns and the relation to firm size

Table 4.3 estimates separate effects for firms in the top quintile of NYSE market cap. Recall from earlier that portfolios formed on share repurchases of firms in the top quintile of NYSE market cap did not measurably earn positive abnormal returns. Estimated alpha was near zero. Consistent with that prior result, regression (2) shows that overall, large firms do not have positive, abnormal daily returns if a month with positive repurchases occurred in the last 90 days.

Regression (4) though shows a filing date effect is still there though for large, repurchasing firms. The lack of significance on the triple interaction term shows that the filing date effect for top size quintile firms is not statistically distinguishable from the filing day effect for smaller firms.

Table 4.3: Share repurchases, market cap, and timing of abnormal returns

Let AR_{it} denote the daily abnormal return of firm i on date t based on the Fama-French five factor model. Abnormal returns are based on monthly betas estimated from a rolling window 30 months to 6 months prior to date t . This table shows estimates of a panel regression of AR_{it} on various indicator variables. $RepurchaseLast90Days_{it}$ takes the value 1 if the 90 days prior to t overlaps a month in which firm i repurchased shares. $NearEarningsDate_{it}$ takes the value 1 on an earnings announcement date and any of the following five days of trading. $NearFilingDate_{it}$ does the same but for the first availability of a quarterly filing on the SEC's EDGAR system. $TopNYSEQuintile_{it}$ is 1 if firm i is in the top NYSE market capitalization quintile in the month prior to day t . All coefficients have units of daily abnormal returns, reported in basis points (i.e. hundredths of a percentage point). The sample covers 2005 through 2015 and includes only firms with publicly announced repurchase programs. Standard errors are clustered by date because of cross-sectional correlation. Standard errors are in parenthesis. One, two, and three stars denote significance at the 5%, 1%, and .1% level respectively.

	(1) FF5	(2) FF5	(3) FF5	(4) FF5
RepurchaseLast90Days	1.16* (0.53)	1.54** (0.57)	1.03 (0.58)	0.92 (0.59)
TopNYSEQuintile		0.03 (0.82)	0.29 (0.84)	0.44 (0.86)
RepurchaseLast90Days \times TopNYSEQuintile		-1.91* (0.81)	-2.07* (0.83)	-1.71* (0.84)
NearFilingDate			-0.70 (1.80)	-2.80 (1.90)
RepurchaseLast90Days \times NearFilingDate			6.31** (1.92)	6.12** (2.01)
NearFilingDate \times TopNYSEQuintile			-3.56 (2.87)	-2.19 (2.99)
RepurchaseLast90Days \times NearFilingDate \times TopNYSEQuintile			2.27 (3.20)	3.14 (3.29)
NearEarningsDate				6.18** (1.93)
RepurchaseLast90Days \times NearEarningsDate				1.38 (2.06)
NearEarningsDate \times TopNYSEQuintile				-2.79 (3.22)
RepurchaseLast90Days \times NearEarningsDate \times TopNYSEQuintile				-4.52 (3.68)
Observations	3254385	3254385	3254385	3254385
Clusters	2897	2897	2897	2897

Chapter 5

Forecasting share repurchases using machine learning

Like an earnings surprise is the difference between actual earnings and forecast earnings, a share repurchase surprise would be the difference between actual repurchases and forecast repurchases. If the market is reacting to new information about share repurchases on information disclosure days, then markets should be reacting to the unexpected component of share repurchases, the share repurchase surprise.

A naive view is that all share repurchases are transient, near unforecastable. This view would not be consistent with modern data. Many firms make consistent repurchases, possibly as a dividend substitute (Skinner 2008, Grullon and Michaely 2004). On earnings calls, firms even speak of share repurchase guidance: “our share repurchase guidance for fiscal 2017 remains unchanged at approximately \$450 million,” or “going forward, we’ve guided to about \$500 million of share repurchase for the rest of the year.”

I use machine learning techniques to produce a forecast of share repurchases and then decompose actual repurchases into an expected and unexpected component. The idea here is pure forecasting, to develop some statistical estimate of what the market might expect based upon avail-

able information. I want to fit a flexible functional form for expected repurchases that is consistent with the different theories and not to commit to a particular economic theory of share repurchases. The features I use for forecasting will be motivated by financial theory and past literature, but I will not place strong constraints upon the functional form. Expected repurchases under numerous different economic theories (eg. to solve free cash flow problems, dividend substitution, or agency issues related to growing earnings per share) will get picked up to some extent by these forecasting regressions.

For appropriate questions, using a purely statistical model has a long history in finance. Fama used the statistical, market model of returns back in the 1960s when he didn't want to place a restriction on the cross-section of expected returns. In more modern times, we regularly use a purely statistical vector auto-regression to model the consumption process rather than an economic theory based, dynamic stochastic general equilibrium model. Purely statistical, machine learning techniques would be inappropriate to determine some causal mechanism here. But purely statistical, machine learning techniques are perfectly appropriate for forecasting in this setting.

The basic machine learning regression paradigm is to fit an extremely flexible functional form to voluminous training data but with a penalty for model complexity (known as regularization). A consistent estimate of model performance is then obtained by applying the estimated model to independent test data. For model selection, I use Compustat annual data prior to 2005. The final forecasts for years 2005 onwards that I use to estimate market reaction will be out of sample forecasts where the model is trained on prior data and where the regularization parameters are chosen based upon 10-fold cross validation on data prior to 2005. All estimation is performed in Python using the Sklearn, Pandas, and Statsmodels packages.

5.1 Features for forecasting

I start with variables identified in Dittmar (2000) as predictive of share repurchases, and supplement with other features I form from the Compustat annual file. I use log market equity, log book assets, book leverage, cash to market equity, book equity to market equity, operating profitability, share repurchases to market equity, dividends to market equity, free cash flow to market equity, earnings to market equity, prior 12 month returns, three years of lags of all the previous variables and all terms in a 2nd degree multivariate polynomial of all these features. I winsorize the original features at the 1 percent level and standardize all features based upon data before 2005. I make sure that all out of sample forecasts from 2005 onwards are nowhere a function of future information.

The key idea is to use a broad enough set of features and a flexible enough functional form so as to build a reasonable proxy for whatever the market might expect of share repurchases under numerous different theories of what causes share repurchases. For example, the features and functional form are perfectly capable of picking up that free cash flow minus dividends matters rather than simply free cash flow, as would be the case under sticky dividend theories that go back to Lintner (1956).

5.2 Machine learning regression models

The models I will consider are ridge regression, LASSO regression, elastic-net regression, random forest regression, and ordinary least squares regression using a subset of variables selected through LASSO.

Ridge regression, also known as Tikhonov regularization, is ordinary least squares plus a penalty term proportional to the squared L_2 norm of the coefficient estimate. If all regressors are uncorrelated, ridge regression estimates are simply the OLS estimates scaled down by a constant factor, and Ridge is equivalent to Bayesian maximum a posteriori estimation with a prior of a zero coefficient vector. The regularization parameter in some sense captures the strength of the

prior. LASSO regression is ordinary least squares plus a L_1 norm penalty instead of the L_2 penalty of ridge (with uncorrelated right hand side variables, LASSO shifts rather than scales coefficient estimates towards zero). Elastic net combines the L_2 norm of ridge regression with the L_1 norm of LASSO. Random forest fits numerous decision trees over different subsets of features and averages the separate forecasts together.

Random forest regression builds decision trees, meaning that only the original 50 or so features need be considered (rather than the approximately 2500 quadratic interactions). Random forest is invariant to monotonic transformations. As is standard, I use regularization to penalize overfitting. Random forest is limited in its tree depth and number of features examined by parameters chosen in cross-validation.

5.3 Variable selection with LASSO

Turning up the regularization parameter on LASSO allows one to accomplish variable selection by examining which variables obtain non-zero coefficients. Turning up the regularization parameter to select eleven features, I find the features selected through LASSO are repurchases to market equity, the square of log market equity, log market equity times repurchases to market equity, log market equity times free cash flow to market equity, log market equity times EBIT to market equity, log market equity times the lag of repurchases to market equity, lagged log market equity times the two year lag of repurchases to market equity, log market equity times the three year lag of repurchases to market equity, repurchases to market equity times the log 12 month return, and repurchases to market equity times three year lagged repurchases to market equity. These particular features should not be taken as gospel. In the presence of correlated features, LASSO can be unstable in which features are picked out in finite samples.

I will use these eleven variables to construct a simplified ordinary least squares based forecast. It turns out the OLS forecast with these eleven variables will have a correlation of .93 with the

broader elastic-net forecast. I will emphasize the elastic-net forecast because its predicted out of sample performance is higher, but generally all the results will go through with the simpler OLS forecast, though the results may be somewhat less sharp.

5.4 Selecting regularization and model hyper-parameters through cross-validation

I perform 10-fold cross-validation on data prior to 2005 with each fold a fiscal year to choose regularization parameters for ridge, lasso, and elastic net and to choose the max depth and maximum features for random forest. Folds are by fiscal year.

The parameters chosen through cross-validation for elastic-net end up giving an extremely tiny L_2 norm penalty, making the elastic-net regression quite close to the LASSO regression. For random forest, a maximum depth of 7 and maximum of 47 percent of features at each split ends up performing best.

5.5 Out of sample forecasts

To construct the share repurchase surprise, I produce repurchase forecasts for fiscal years 2005 through 2017 based upon models fit on a rolling window of data from fiscal year $t - 17$ to $t - 2$ and using the parameters chosen in the earlier cross-validation. An upper bound of $t - 2$ is used in training to clearly avoid any time-series contamination, of in any way using the future to forecast the past. The full design matrix of all quadratic interactions is about a gigabyte in size.

Since the elastic net forecast had the best cross-validation performance, that is the model I will apply moving forward in future sections. For completeness/robustness, I also generate out of sample forecasts using all the other models from 2005 through 2017. The year by year performance is shown in figure 5.1. Generally, all results go through with the simpler, OLS based estimate.

Elastic-net continues to perform the best out of sample, as it was predicted to do based upon performance in cross-validation. The other models though are competitive. Even simplified OLS model with variables chosen through LASSO variable selection does reasonably well. Forecast performance completely falls apart during the financial crisis, which shouldn't be surprising. Nothing in the training data or features available (from the previous fiscal year) for forecasting allows me to forecast the massive collapse in repurchases that occurs during the financial crisis. High dimensional machine learning techniques allow you to better forecast by learning more subtle patterns in data, but it does not allow one to magically see around corners.

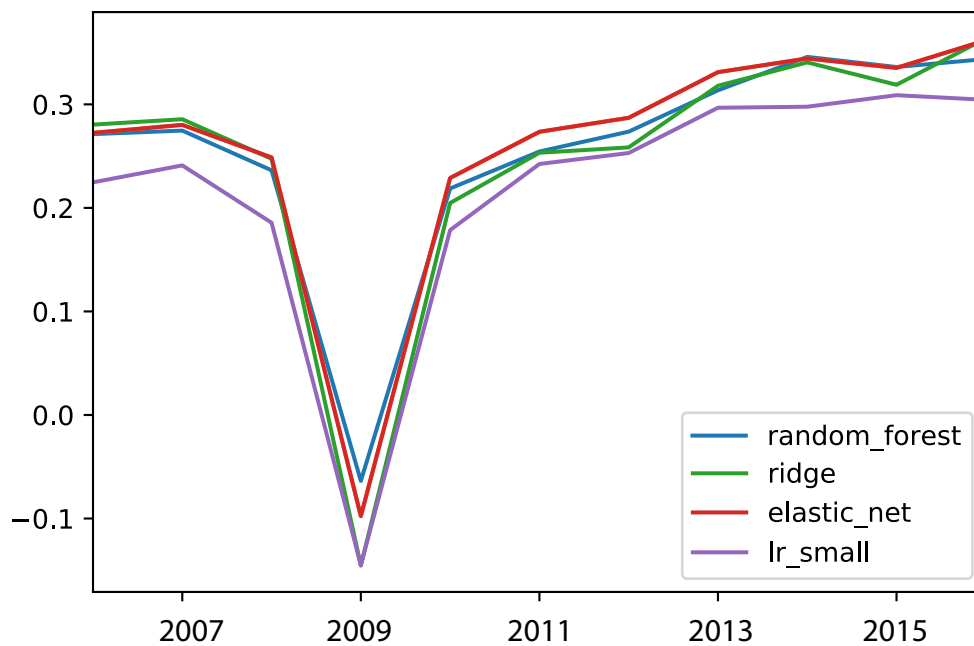


Figure 5.1: Out of sample repurchase forecast scores

This figure shows out of sample forecast scores for various machine learning regression models by year. Model parameters are chosen by cross-validation on 1995 to 2004 with splits by fiscal year. Forecasts for fiscal year y are formed using a model fit on training data from fiscal year $y - 17$ to $y - 2$. lrsmall is the ordinary least squares model with eleven features described in the text.

Chapter 6

The share repurchase surprise: market reaction to unexpected repurchases

Armed with out of sample forecasts of share repurchases developed in the previous section, I decomposes repurchases into an expected and unexpected component, the unexpected component being the share repurchase surprise.

$$\underbrace{X_t}_{\text{repurchases}} = \underbrace{E[X_t | \mathcal{F}_{t-1}]}_{\text{expected repurchases}} + \underbrace{X_t - E[X_t | \mathcal{F}_{t-1}]}_{\text{unexpected repurchases}}$$

The question is whether unexpected share repurchases better explains abnormal returns around earnings announcements and 10-Q, 10-K filings than raw repurchases. As a left hand side variable, I have daily abnormal returns around earnings announcement and 10-Q, 10-K filing days as computed under the Fama-French five factor model. The sample is restricted to firms with outstanding share repurchase authorizations as reported in the 10-Q or 10-K, and repurchases larger than 5 percent are excluded as they're largely tender offers or other types of transactions. The repurchase fraction is the number of shares repurchased as a fraction of prior shares outstanding.

Table 6.1: Share repurchases, unexpected repurchases, and abnormal returns near filing or earnings date

This table shows the result of regressing daily abnormal returns (measured in basis points) near earnings announcement days or 10-Q or 10-K EDGAR filing days on the fraction of shares repurchased in a quarter, the unexpected fraction of shares repurchased in quarter, and various earnings surprise controls. A day is considered near an earnings announcement or a filing date if it is on the date or up to five trading days after. Abnormal returns are computed using the Fama-French five factor model with betas estimated on monthly data from 30 months to 6 months prior to the day. Basic earnings controls include an indicator for a negative earnings surprise, the surprise as a fraction of share price, and the square of the surprise fraction. Advanced controls include interactions with log market cap. The sample covers 2005 through 2015 and includes only firms with publicly announced repurchase programs. The unexpected repurchase fraction is computed by subtracting an out of sample forecast of share repurchases computed using three prior years of 10-K data and coefficients estimated with elastic net regression. Repurchases are excluded if more than five percent of market cap. Standard errors are clustered by date because of cross-sectional correlation. Standard errors are in parenthesis. One, two, and three stars denote significance at the 5%, 1%, and .1% level respectively.

Panel A: Full sample

	(1)	(2)	(3)	(4)	(5)	(6)
	FF5	FF5	FF5	FF5	FF5	FF5
RepurchaseFraction	287.57*** (68.41)		-221.60 (176.88)		-403.32* (179.09)	
UnexpectedRepurchaseFraction		367.40*** (73.63)	579.41** (189.98)	319.56*** (78.36)	704.16*** (192.51)	310.05*** (78.57)
Basic Earnings Controls	No	No	No	Yes	Yes	Yes
Full Earnings Controls	No	No	No	No	No	Yes
Observations	275082	275082	275082	246084	246084	246084
Clusters	2678	2678	2678	2676	2676	2676

Panel B: Financial crisis January 2008 to July 2009

	(1)	(2)	(3)	(4)	(5)	(6)
	FF5	FF5	FF5	FF5	FF5	FF5
RepurchaseFraction	419.08 (224.83)		-708.57 (704.50)		-661.19 (720.47)	
UnexpectedRepurchaseFraction		571.44* (222.34)	1221.54 (698.58)	344.56 (240.58)	948.69 (709.76)	324.17 (243.37)
Basic Earnings Controls	No	No	No	Yes	Yes	Yes
Full Earnings Controls	No	No	No	No	No	Yes
Observations	42947	42947	42947	37185	37185	37185
Clusters	399	399	399	399	399	399

Table 6.1 shows the results. Model (1) and (2) shows the raw association between repurchases and abnormal returns and unexpected repurchases and expected returns respectively. The estimate

of 367 shows that an unexpected repurchase of 1% of market cap in a quarter would be associated with 3.7 basis points of abnormal returns per day for the earnings announcement or the 10-Q or 10-K filing date and five subsequent trading days.

Model (3) conducts a horse race, and the regression puts all the effect on unexpected repurchases, driving the coefficient on raw repurchases to statistical insignificance. Models (4), (5), and (6) add robust earnings surprise controls, showing the effect isn't merely operating through a relationship to the current earnings surprise. For earnings controls, I include an indicator for a negative earnings surprise, the surprise as a fraction of the share price, the square of that fraction, and interactions with whether the date is near the earnings date. Full controls also include interactions with the logarithm of prior market cap. Standard errors are clustered by date because of cross-sectional correlation. Panel B of breaks out the great recession, financial crisis period. The estimates are larger here but also are poorly estimated because of the short sample.

6.1 Can the unexpected share repurchase announcement effect significantly be linked to proxies for information asymmetry or average q?

Under a market misvaluation, asymmetric information theory of share repurchases, one might expect the market reaction to disclosure of share repurchase news to be stronger for firms with higher degrees of information asymmetry. Under an agency cost of free cash flow theory (Jensen 1986), one might expect a stronger reaction to share repurchases surprises for firms with high agency costs of free cash flow. For example, Lang and Litzenberger (1989) explored these competing theories in the context of dividend announcements.

Using different proxies for information asymmetry and agency costs of free cash flow though, I'm unable to detect statistically significant, robust effects (possibly due to lack of power). Table

6.2 takes the approach of table 6.1 but adds interactions of the unexpected repurchase effect with various covariates. The regressions here fail to detect a synergistic or antagonistic effect that is robust and significant.

The first series of covariates are proxies for information asymmetry. The first covariate I consider is an indicator for the top quintile of NYSE market cap. Firm size is overwhelmingly related to all kinds of information asymmetry proxies: eg. liquidity measures such as Amihud (2002) liquidity, analyst coverage, idiosyncratic volatility, financial constraints, etc. . . . The second and third variables are indicators for the biotech industry and drug industry respectively, two industries with huge potential asymmetry between the information sets of insiders and outsiders.

The estimated interaction with firm size is modestly negative, but the result is not statistically significant over this six day period. In unreported results, the coefficient does show up as significantly negative if the window is extended to ten days past the earnings and filing date rather than five. The estimated coefficient on the biotech industry is insignificant and goes the wrong way from expected under the theory that biotech firms have higher information asymmetry and that share repurchases may signal insider knowledge.

The last two covariates are motivated by Q theory and agency costs to free cash flow of Jensen (1986). If low Tobin's Q proxies for over investment, returning cash may increase firm value for low Q firms (Lang and Litzenberger 1989). I find, no detectable difference though between high market to book and low market to book firms. This is consistent with Howe et. al. (1992) which found no relation between reaction to self tender offers for high and low Q firms. Peters and Taylor (2017) argue intangible capital is mismeasured in book value. I try their measure TotalQ but again find no significant effect.

Table 6.2: Variation of share repurchase announcement effect

This table shows the result of regressing daily abnormal returns (measured in basis points) near earnings announcement days or 10-Q or 10-K EDGAR filing days on the fraction of shares repurchased in a quarter, the unexpected fraction of shares repurchased in quarter, and various earnings surprise controls. A day is considered near an earnings announcement or a filing date if it is on the date or up to five trading days after. Abnormal returns are computed using the Fama-French five factor model with betas estimated on monthly data from 30 months to 6 months prior to the day. Basic earnings controls include an indicator for a negative earnings surprise, the surprise as a fraction of share price, and the square of the surprise fraction. Advanced controls include interactions with log market cap. The sample covers 2005 through 2015 and includes only firms with publicly announced repurchase programs. The unexpected repurchase fraction is computed by subtracting an out of sample forecast of share repurchases computed using three prior years of 10-K data and coefficients estimated with elastic net regression. Repurchases are excluded if more than five percent of market cap. Standard errors are clustered by date because of cross-sectional correlation. Standard errors are in parenthesis. One, two, and three stars denote significance at the 5%, 1%, and .1% level respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	FF5	FF5	FF5	FF5	FF5	FF5	FF5	FF5	FF5	FF5
UnexpectedRepurchaseFraction	397.4** (88.1)	320.7*** (93.7)	368.0*** (74.1)	312.4*** (79.0)	361.7*** (74.0)	304.5*** (79.1)	275.5* (113.2)	192.6 (115.3)	301.2** (112.0)	254.8* (116.2)
UnexpectedRepurchaseFraction \times TopSizeQuintile	-124.3 (126.1)	-44.5 (137.0)								
UnexpectedRepurchaseFraction \times Biotech Industry			-48.7 (553.2)	-200.2 (565.2)						
UnexpectedRepurchaseFraction \times DrugIndustry					224.4 (406.2)	214.4 (418.0)				
UnexpectedRepurchaseFraction \times LogMarketToBook							98.9 (100.5)	120.9 (104.0)		
UnexpectedRepurchaseFraction \times PetersTaylorTotalQ									71.4 (61.2)	67.9 (63.4)
Basic Earnings Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Full Earnings Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	275082	246084	275082	246084	275082	246084	271458	242970	250506	223458
Clusters	2678	2676	2678	2676	2678	2676	2678	2676	2678	2676

Chapter 7

Is firm repurchase behavior consistent with trying to time the market?

In surveys, managers say they try to repurchase undervalued shares, but might this be meaningless talk? Do firms behave as if they were trying to time the market? In this section, I will test for the kinds of patterns that might arise if a firm had some target price in mind when repurchasing shares.

7.1 Fraction of shares repurchased and prior cumulative abnormal returns

If management believes a decline in the share price is unwarranted, they may respond by increasing share repurchases. Thus, a negative association between prior returns and share repurchases would be consistent with a market timing motive. Of course though, there are other theories which would induce such a correlation. A negative shock to investment opportunities may lower firm value and increase benefits of paying out cash. A shock to discount rates could do similar: rising discount rates drive firm value down and increase the benefits of returning cash to investors (so the cash may be deployed elsewhere).

I find negative, 30-day cumulative abnormal returns in the period preceding a month with share repurchases forecasts larger repurchases. Furthermore, this effect is strongest for the most immediate 30 day period compared to earlier 30 day periods: 1-30 day lagged CAR is a stronger predictor than 31-60 day lagged CAR. Extremely recent, negative, risk-adjusted returns forecast significantly higher repurchases. But positive abnormal returns don't. I use risk-adjusted returns to help the alleviate concern that the effect is driven by aggregate shocks to discount rates. Stephens and Weisbach (1998) used quarterly data and found a negative relationship between prior returns and repurchases in a quarter. Using a short sample of monthly data, Bozanic (2009) estimated a negative relationship between prior returns and the fraction of shares repurchased, but did not find a statistically significant result. Ben-Raphael et. al. (2013) use a probit model and find that negative returns in earlier months forecast a higher probability of a firm repurchasing more than zero shares.

I form cumulative abnormal returns for the 30 days preceding a month in which a firm repurchases using the Fama-French three factor model as the model of expected returns.

Table 7.1: Repurchase fraction and Fama-French three factor cumulative abnormal return in prior 30 days

$\text{Log}(\text{RepurchaseSize})$ is the logarithm of the fraction of prior market cap repurchased in a month. $\text{CAR}(\text{FF3})$ is the cumulative abnormal return under the Fama-French three factor model for the 30 days *previous* to the share repurchase period (see Appendix for precise details on how $\text{CAR}(\text{FF3})$ is formed). $\text{CAR}(\text{FF3})+$ is the cumulative abnormal return only if the cumulative abnormal return is positive, otherwise it is zero. $\text{CAR}(\text{FF3})-$ is the cumulative abnormal return only if the cumulative abnormal return is negative. Standard errors are clustered at the firm level. Standard errors are in parenthesis. One, two, and three stars denote significance at the 5%, 1%, and .1% level respectively.

	(1)	(2)	(3)
	$\text{LogRepurchaseFraction}$	$\text{LogRepurchaseFraction}$	$\text{LogRepurchaseFraction}$
$\text{CAR}(\text{FF3})$	-0.832*** (0.098)	-0.807*** (0.084)	
$\text{CAR}(\text{FF3})+$			-0.030 (0.173)
$\text{CAR}(\text{FF3})-$			-1.597*** (0.164)
Firm Fixed Effects	No	Yes	Yes
Observations	31496	31496	31496
R2	0.003	0.005	0.007

We can see from Table 7.1 that there is a significant, negative correlation between the fraction of market cap repurchased and the 30-day trailing cumulative abnormal return. Specification (2) adds firm fixed effects, thereby utilizing within firm time-series variation. Specification (3) breaks the cumulative abnormal return into two components. $\text{CAR}(\text{FF3})+$ is equal to the cumulative abnormal return if the return is positive and zero if the return is negative. And $\text{CAR}(\text{FF3})-$ is equal to the cumulative abnormal return if the return is negative and zero if the return is positive. From specification (3) of table 7.1 we can see it is the negative return that matters. Positive cumulative abnormal returns don't forecast less repurchasing, but negative cumulative abnormal returns forecast more repurchasing.

I can reverse the left hand side and the right hand side of the regression and show how the prior

cumulative abnormal return varies with the size of the repurchase.

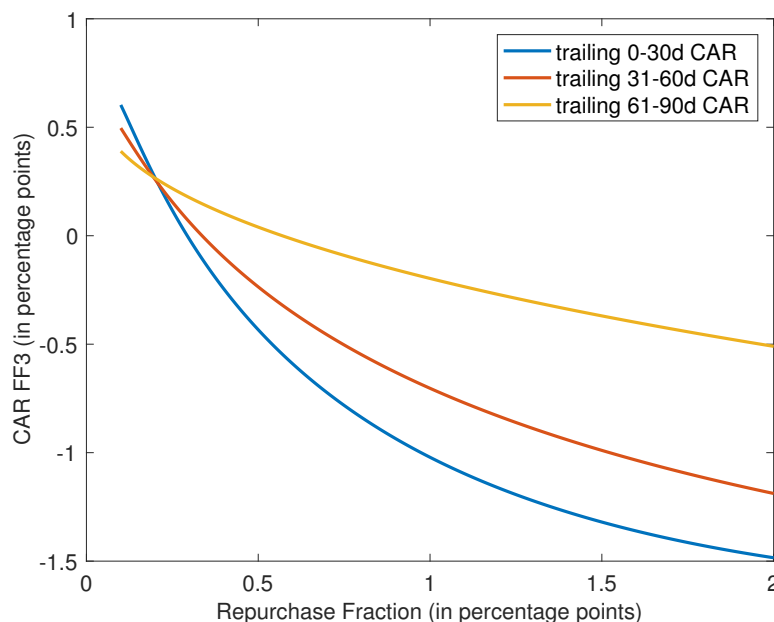


Figure 7.1: Prior cumulative abnormal return and repurchase fraction

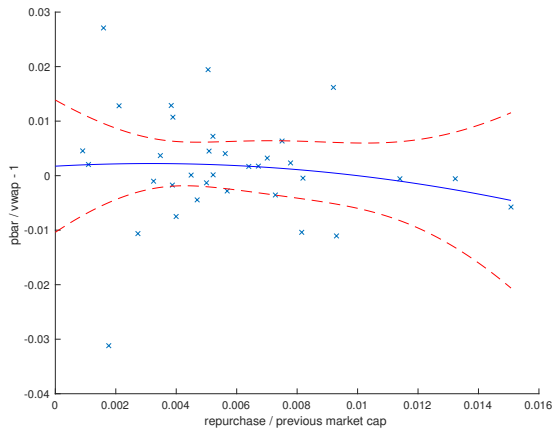
This figure shows a polynomial curve fit between the fraction of shares repurchased in a month and trailing cumulative abnormal returns. Let t denote the start of the month. The three curves are based on cumulative abnormal returns from $t-30$ to t , $t-60$ to $t-30$, and $t-90$ to $t-60$. Cumulative abnormal returns are the sum of daily abnormal returns. Daily abnormal returns are calculated using the Fama-French three factor model based on betas estimated using returns from 30 to 6 months prior to the day in question.

Figure 7.1 shows the results for cumulative abnormal returns over 1 to 30 days prior, 31 to 60 days prior, and 61 to 90 days prior. I fit a polynomial curve to each relationship. We can clearly see that the relationship is strongest for more recent cumulative abnormal returns. A repurchase of 1 percent of market cap is associated with approximately a 1 percent cumulative abnormal return over the prior 30 days. The relationship between repurchases and prior cumulative abnormal returns is strongest for cumulative abnormal returns over the most recent period.

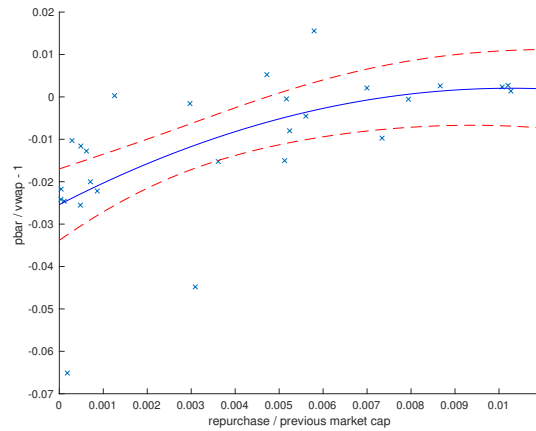
7.2 Evidence from the relation between repurchase fraction and price paid for repurchases in a month

Based upon anecdotal conversations, some firms say they come up with some valuation for their share price, eg. by discounted cash flows (DCF), and repurchase shares if the market price is below their DCF price. Mechanically, this behavior would lead to a correlation between the number of shares repurchased in a month and the percent difference between the average price paid for repurchases and the volume weighted average price for the month. For intuition, imagine a firm repurchases at a constant rate whenever the stock price is below 10. If the stock price starts below 10 and stays below 10 for the entire period, the firm will repurchase many shares at the average price of the period. If the stock price starts above 10 and drifts below or starts below drifts above 10 etc..., the firm will repurchase fewer shares at an average price below the average price of the period.

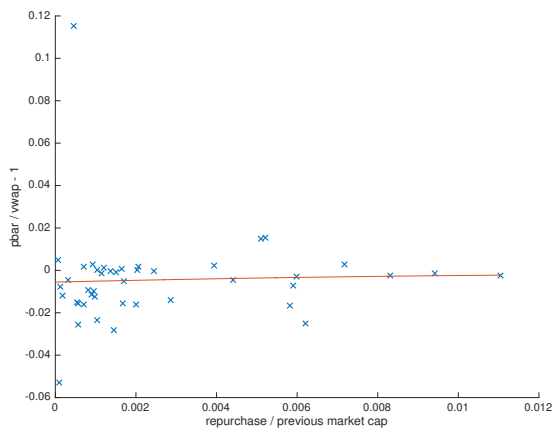
I will now test for the presence of this correlation. Let X_{it} be the average price paid for shares by firm i in period t . Let $VWAP_{it}$ be the volume weighted average price for firm i in period t . As in Ben-Rephael et. al. (2013), let $DIFF_{it} = \frac{X_{it}}{VWAP_{it}} - 1$. Let A_{it} be the fraction of market-cap repurchased. A limit order when repurchasing shares mechanically will induce a positive correlation between repurchase fraction A_{it} and $DIFF_{it}$.



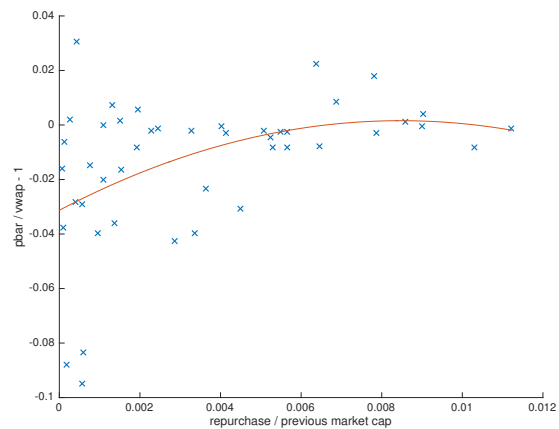
(a) Firm A is known to not base repurchase decisions on the current share price



(b) Firm B is known to base repurchase decisions on the current share price



(c) Costco



(d) Starbucks

Figure 7.2: Examples of repurchase fraction vs. difference with VWAP

This figure shows, for four firms, the relation between the fraction of prior market cap repurchased by a firm and the percent difference between the average price for shares within a month and the volume weighted average share price for the month.

Let me give an empirical example. Figure 7.2a shows the relation between repurchase fraction A_t and $DIFF_t$ for a company whose management said they *do not* look at the share price when deciding how many shares to repurchase, and observe that there is no measurable link between repurchase fraction A_t and $DIFF_t$. In contrast, Figure 7.2b shows the relation between fraction of market cap repurchased A_{it} and $DIFF_{it}$ for a firm whose management has said they *do* pay attention to the share price. These are real, actual firms. Observe the significant, positive correlation between

the fraction of market cap repurchased and the discount to volume weighted average price of the period.

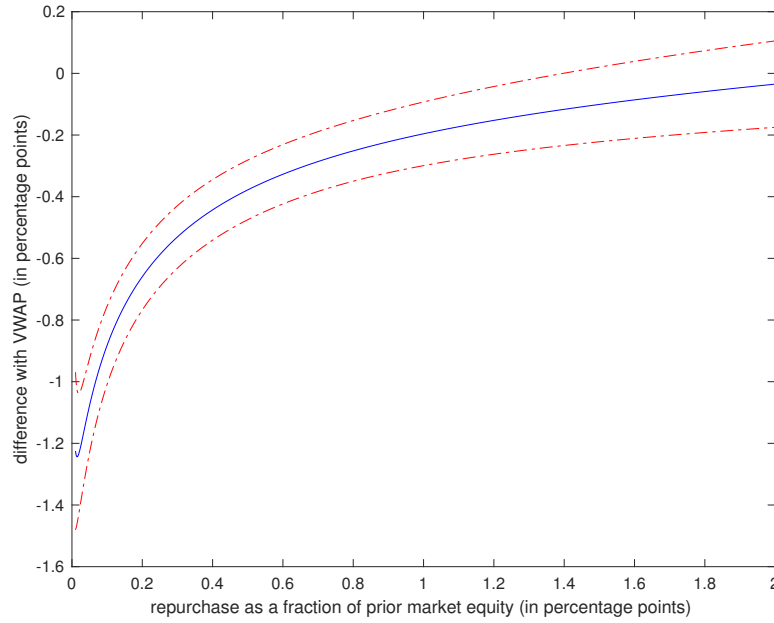


Figure 7.3: Repurchase fraction vs. diff

This figure shows a polynomial fit of the fraction of prior market capitalization repurchased in a month versus $\frac{\bar{P}}{VWAP} - 1$, the percentage difference between the average price paid for repurchases and the volume weighted average stock price. Dotted lines show the 95 degree confidence interval based upon standard errors clustered by date.

Turning to the full data, Figure 7.3 shows the relation between the repurchase fraction A_{it} and the discount to the volume weighted average price, $DIFF_{it}$, equally weighting all firm-months. Observe the robust, positive relation between the repurchase fraction and $DIFF_{it}$. Whatever the trading strategies are that generate this pattern, we can overwhelmingly reject the hypothesis that the repurchase process is unrelated to the price process within a month. Almost certainly for many firms, how much a firm repurchases in a month depends on the price path within the month. The lower the price goes, the more firms tend to repurchase.

Figure 7.4 charts a surface showing how $DIFF_{it}$ varies by the repurchase fraction and log firm size. The surface is fit to a fourth order polynomial over the variables. The relationship between the repurchase fraction and $DIFF_{it}$ is strongest for firms with about a billion dollar market cap.

Figure 7.5 shows how the return to the end of the month varies with the repurchase fraction.

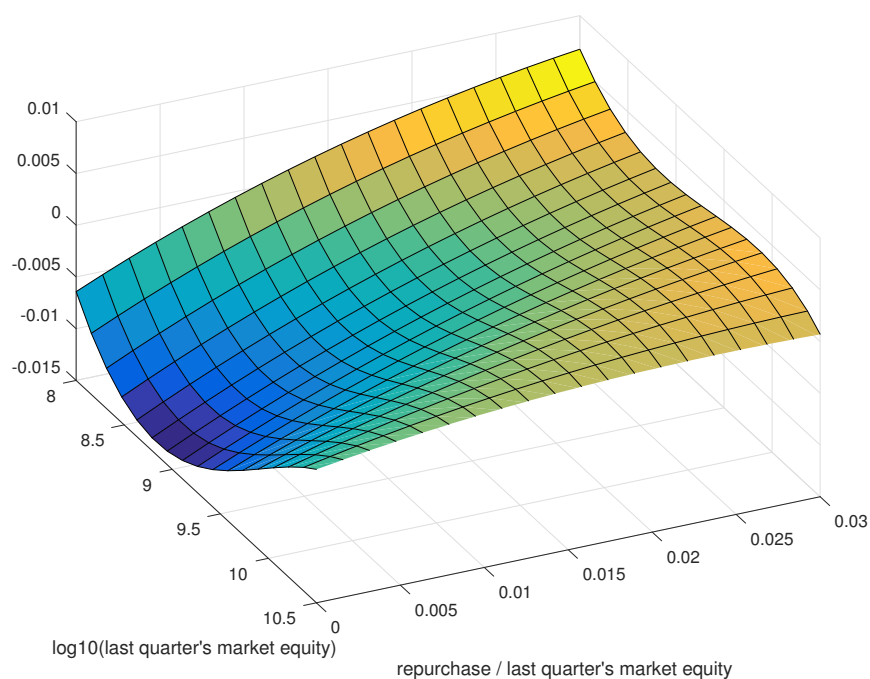


Figure 7.4: Repurchase fraction and log size vs. diff

This figure shows a 4th order multi-variate polynomial fit of $\frac{P}{VWAP} - 1$, the percentage difference between the average price paid for repurchases and the volume weighted average stock price, as it varies with: (i) the fraction of prior market capitalization repurchased in a month as it varies with (i) and (ii) the base 10 log of the firm's market previous market capitalization. Eg. 9 denotes a $10^9 = 1$ billion dollar firm and 8 denotes a $10^8 = 100$ million dollar firm.

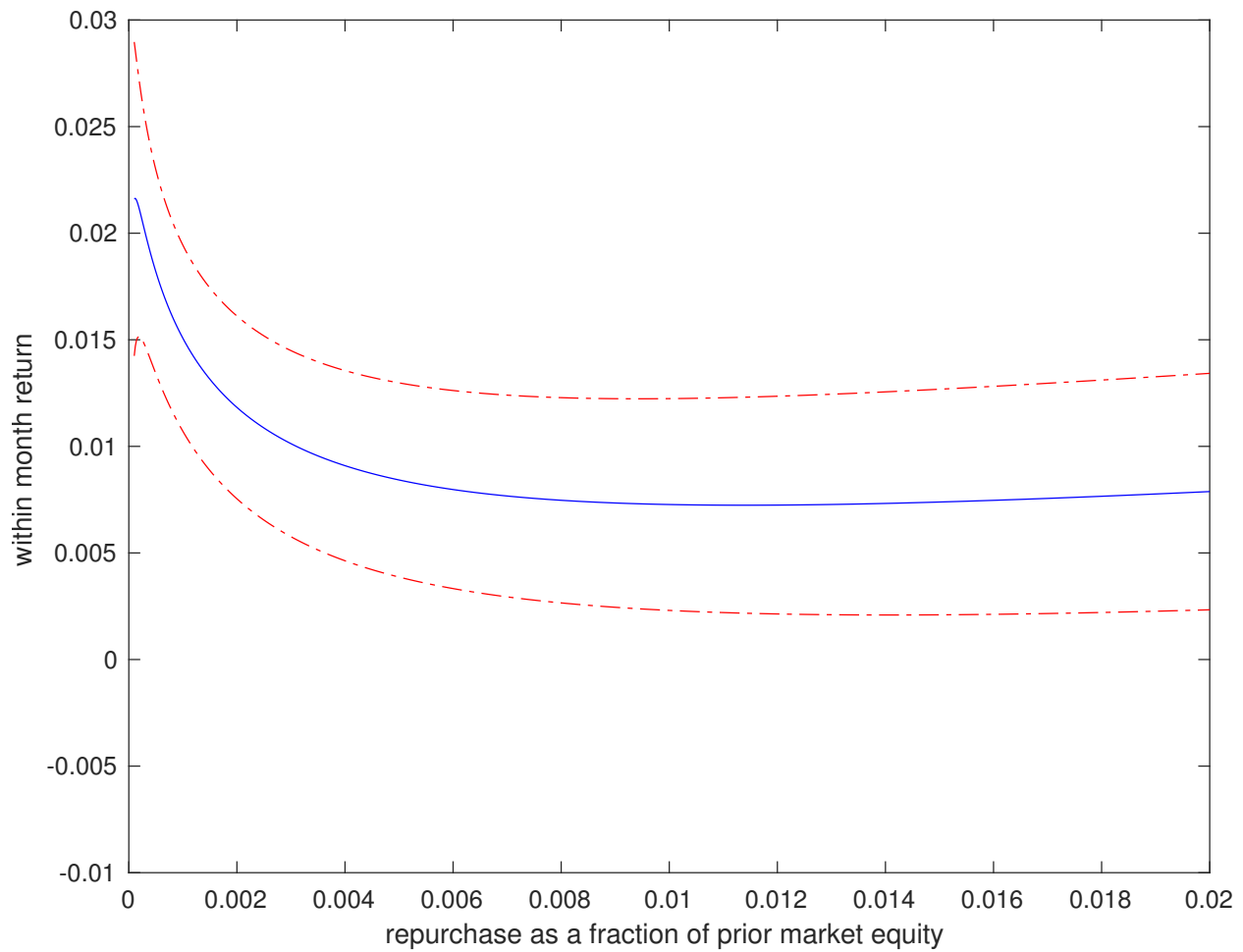


Figure 7.5: Polynomial fit of repurchase fraction vs. within month return on share repurchases

This figure shows a polynomial fit of the repurchase fraction (x-axis) to the end of month price divided by the average price paid for share repurchases within the month (y-axis). A fifth degree polynomial is fit with least squares, and the dotted lines show the 95 percent confidence interval based upon standard errors clustered by date.

Chapter 8

Do firms acquire shares at unusually low prices?

The prior literature has said yes, but with my methodology I obtain substantially smaller estimates for the difference between the average price paid in a month and various benchmarks. Furthermore, a perhaps intractable challenge in this analysis is to construct a reasonable null hypothesis; different uninformed (about the future) trading strategies can lead to different expectations for the average acquisition price of shares relative to volume weighted average price.

Let $\bar{X}_{i,t}$ be the average acquisition price of shares reported by firm i for month t (i.e. the value parsed from tables similar to Figure 2.2). To answer the first question, I will follow the prior literature and compare average acquisition price $\bar{X}_{i,t}$ with various benchmarks. I will differ though by weighting firm-months by the repurchase fraction. If a firm repurchases 1% of market cap in January and 0.01% in February, then January will have 100x the weight of February since 100x as many shares were repurchased. Repurchase fraction weighting rather than equal weighting is important because from figure 7.3 we know that tiny repurchases are associated with a large discount to the volume weighted average price (and a larger return to the end of month share price).

Let $P_{i,t}^e$ be stock price of firm i in month t at the end of the month. Let $\bar{P}_{i,t}^v$ be the volume weighted average price of firm i in month t . I will define three benchmarks:

- Define $RET_{it} = \bar{R}_{i,t} = \frac{P_{i,t}^e}{\bar{X}_{i,t}} - 1$. This is the mean arithmetic return (to the end of the month) of repurchases made in the month. Note that you don't know the holding period.
- Define $RELREP_{i,t} = \frac{\bar{X}_{i,t}}{P_{i,t}^e} - 1$ as the relative repurchase price as in Dittmar and Field (2015). This measure has been used in the prior literature. It is an inverse measure, lower values imply lower average acquisition prices and higher returns. Also by Jensen's inequality, $1 + E[RELREP_{i,t}] < 1/E[1 + RET_{it}]$ (because $1/x$ is a convex function).
- Define $DIFF_{i,t} = \frac{\bar{X}_{i,t}}{\bar{P}_{i,t}^v} - 1$ as the percent difference with the volume weighted average price as in Ben-Rephael et. al. (2013). Again, this is an inverse measure. A lower value implies shares are acquired at lower prices relative to the volume weighted average price of the period. This measure too has been used in the prior literature.

I will compute the average values for these measures two ways: (i) equally weighting each firm-month (for comparison purposes) and (ii) weighting firm-months by the dollar value of the repurchase relative to the firm's market cap. I refer to the dollar value of the repurchase divided by lagged market cap as the repurchase fraction.

Table 8.1: Comparison of repurchase price to several benchmarks

$DIFF_{it}$ measures the average price paid X_{it} relative to the volume weighted average price; values lower than zero imply shares were on average acquired at a discount. The relative repurchase price $RELREP_{it}$ measures the average price paid X relative to the period ending price; lower values imply shares were on average were acquired at a lower price than at month end. RET_{it} is the average return on the repurchases to the end of the month. By Jensen's inequality $1 + E[RELREP_{i,t}] < 1 / E[1 + RET_{it}]$ (because $1/x$ is a convex function). Units are in percentage points. Standard errors are in parenthesis. Stars denote statistical significance at the 5%, 1%, and .1% level respectively. Standard errors are two-way clustered by firm and calendar date.

	Diff	Diff (weighted)	Rel Rep	RelRep (weighted)	Ret	Ret (weighted)
Full sample	-0.50*** (0.05)	-0.07 (0.07)	-0.61** (0.23)	-0.43 (0.25)	1.11*** (0.23)	1.00*** (0.26)
Repurchase size < 4%	-0.52*** (0.05)	-0.21*** (0.05)	-0.61** (0.23)	-0.36 (0.25)	1.10*** (0.23)	0.85*** (0.25)
Market Cap < 10 billion	-0.57*** (0.05)	-0.23*** (0.06)	-0.66** (0.24)	-0.38 (0.26)	1.21*** (0.24)	0.92*** (0.27)
Market Cap > 10 billion	-0.23*** (0.04)	-0.10* (0.04)	-0.39* (0.19)	-0.24 (0.22)	0.61** (0.19)	0.44* (0.21)

Examining table 8.1, we see that weighting by repurchase fraction reduces the discount relative to the volume weighted average price of the period from 50 basis points to a statistically insignificant 7 basis points. The relative repurchase price (an inverse measure) rises to statistical insignificance. The average return declines by 11 basis points. These are economically significant differences: 25 basis points on a 600 billion base is 1.5 billion.

One reasonable complaint is that incredibly large repurchases within a month are generally modified Dutch auction tender offers, fundamentally different animals than regular open-market repurchases. Among the many differences is that the timing of tender offers is publicly known. Furthermore, large open-market repurchases that are a significant share of trading volume will mechanically be closer to the volume weighted average price (because they become the volume)! The second row of table 8.1 excludes the approximately 1 percent of repurchases that are larger than 4 percent of market cap.

Excluding mega repurchases (i.e. those greater than 4 percent), both the mean return (i.e. RET)

and the relative repurchase price both decrease in magnitude when repurchase fraction weighted rather than equal weighted. As might be expected, the difference with the volume weighted average price increases in magnitude. Different cutoff points (eg. five percent or two percent) don't substantially alter this picture.

The third row of table 8.1 further restricts the sample to stocks with greater than \$10 billion in market cap based upon the closing date of the prior quarter (i.e. large cap stocks). Approximately 80% of the dollar value of share repurchases in a year comes from firms \$10 billion in market cap or above. Looking at only large-cap stocks, all the measures decrease in magnitude even further: the average return falls and the inverse measures *DIFF* and *RELREP* rise towards zero. The repurchase discount effect appears concentrated in small to mid-size firms.

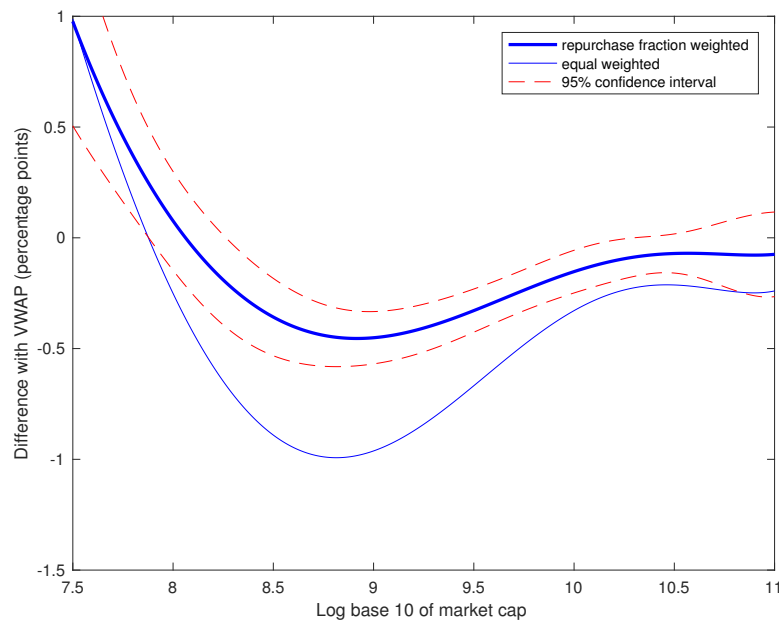
In summary, weighting firm-months by the fraction of shares repurchased rather than equal weighting firm months substantially reduces the estimated discount at which firms repurchase shares. If firms repurchased random amounts at random times, one might expect the discount to the volume weighted average price to be zero. That is clearly not what they do though, and keep in mind that it is still possible for firms to implement uninformed (about the future) trading strategies that achieve discounts to the volume weighted average price even with my weighting if it were a firm objective.

There's also the obvious point though that because stocks tend to appreciate in value, the expected value of *RET* and *RELREP* are not expected to be zero. In some sense, they are measures that need some form of risk adjustment! I present unadjusted numbers though because a precise, proper risk adjustment is in some sense impossible based upon the limited data. It would be highly arbitrary. Adjusting for a full month of returns is in some sense inappropriate because many of the repurchased shares were held for less than a month. Higher returns were likely held for longer and should have a longer risk adjustment. In essence, it's difficult to apply a sensible risk adjustment without a model of how firms trade, and further (unreported results) show that different firms almost certainly follow different trading strategies.

Also, zero discount to VWAP does not necessarily imply no abnormal returns. If there were positive abnormal returns throughout the month and a firm repurchased randomly throughout the month, there would be positive abnormal returns but there would not be a discount to the volume weighted average price.

The null of prior literature in this area has implicitly assumed that firms' repurchase process is uncorrelated with their share price process, but as discussed earlier, a firm issuing a simple limit order will violate this assumption. In the data, the repurchase fractions clearly varies with lagged returns.

Figure 8.1: Difference between average repurchase price and VWAP vs. market cap



This figure shows best fit lines and confidence bands for polynomial regressions of the volume weighted average price (VWAP) on log prior market cap. Seventh degree polynomials are formed based upon the standardized log market cap. Repurchases larger than 4% of market cap are excluded as they generally are modified Dutch auctions or other types of tender offers.

Chapter 9

Conclusion

Using systematic, machine extracted data on monthly share repurchases, I form portfolios based upon repurchases in the prior month and show that large firms do not have abnormals while small and mid-cap firms do. Abnormal returns are largest for repurchase fraction weighted portfolios with holding periods of a few months.

Furthermore, there's evidence that share repurchases in a quarter coincide with positive news or are viewed by markets as positive news. The share repurchase surprise, that is actual repurchases minus a machine learning based forecast of repurchases, is associated with significant positive abnormal returns around the earnings announcement date and 10-Q or 10-K filing date even after controlling for the earnings-surprise. I show that *unexpected* share repurchases convey information to markets.

I also argue that the pattern of share repurchases in the data is consistent with numerous firms trying to time the market. The pattern of average price paid within a month for repurchases and the quantity repurchased is consistent with firms utilizing limit orders or some other price sensitive trading strategy.

Are these the types of returns managers have in mind when conducting share repurchases and answering surveys about their share repurchase programs? Perhaps for small and mid-cap firms.

And markets clearly react to news of unexpected share repurchases. On the other hand, longer term, estimated abnormal returns are remarkably close to zero for the share repurchases of large firms in the top quintile of NYSE market cap. These large firms is where a significant majority of the dollar value of share repurchases lies.

Bibliography

- Amihud, Yakov, 2002, Illiquidity and stock returns: cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.
- Baker, H. Kent, Patricia L. Gallagher, and Karen E. Morgan, 1981, Management's view of stock repurchase programs, *Journal of Financial Research* 4, 233–247.
- Baker, H. Kent, Gary E. Powell, and E. Theodore Veit, 2003, Why companies use open-market repurchases: A managerial perspective, *The Quarterly Review of Economics and Finance* 43, 483–504.
- Banyi, Monica L., Edward A. Dyl, and Kathleen M. Kahle, 2008, Errors in estimating share repurchases, *Journal of Corporate Finance* 14, 460–474.
- Barber, Brad M., Emmanuel T. De George, Reuven Lehavy, and Brett Trueman, 2013, The earnings announcement premium around the globe, *Journal of Financial Economics* 108, 118–138.
- Ben-David, Itzhak, John R. Graham, and Campbell R. Harvey, 2010, Managerial miscalibration, Discussion paper, National Bureau of Economic Research.
- Ben-Rephael, Azi, Jacob Oded, and Avi Wohl, 2013, Do firms buy their stock at bargain prices? evidence from actual stock repurchase disclosures*, *Review of Finance* p. rft028.
- Bonaim, Alice A., Kristine W. Hankins, and Bradford D. Jordan, 2016, The cost of financial flexibility: Evidence from share repurchases, *Journal of Corporate Finance* 38, 345–362.
- Bozanic, Zahn, 2009, Managerial motivation and timing of open market share repurchases, *Review of Quantitative Finance and Accounting* 34, 517–531.
- Brav, A., J. R. Graham, C. R. Harvey, and R. Michaely, 2005, Payout policy in the 21st century, *Journal of Financial Economics* 77, 483–527.
- Brockman, Paul, and Dennis Y. Chung, 2001, Managerial timing and corporate liquidity:: evidence from actual share repurchases, *Journal of Financial Economics* 61, 417–448.
- Chan, Konan, David L. Ikenberry, and Inmoo Lee, 2007, Do managers time the market? evidence from open-market share repurchases, *Journal of Banking & Finance* 31, 2673–2694.

- Cook, Douglas O., Laurie Krigman, and J. Chris Leach, 2003, An analysis of sec guidelines for executing open market repurchases, *The Journal of Business* 76, 289–315.
- De Cesari, Amedeo, Susanne Espenlaub, Arif Khurshed, and Michael Simkovic, 2012, The effects of ownership and stock liquidity on the timing of repurchase transactions, *Journal of Corporate Finance* 18, 1023–1050.
- DeAngelo, Harry, Linda DeAngelo, and Douglas J. Skinner, 2008, Corporate payout policy, *Foundations and Trends in Finance* 3.
- Dittmar, Amy, and Laura Casares Field, 2015, Can managers time the market? evidence using repurchase price data, *Journal of Financial Economics* 115, 261–282.
- Dittmar, Amy K., 2000, Why do firms repurchase stock*, *The Journal of Business* 73, 331–355.
- Evgeniou, Theodoros, Enric Junque de Fortuny, Nick Nassuphis, and Theo Vermaelen, 2016, Volatility and the buyback anomaly, .
- Fama, Eugene F., 1998, Market efficiency, long-term returns, and behavioral finance, *Journal of Financial Economics* 49, 283–306.
- Fama, EF F., and KR R. French, 2008, Dissecting anomalies, *The Journal of Finance* 63, 1653–1678.
- Fama, Eugene F., and Kenneth R. French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1–22.
- Frazzini, Andrea, and Owen A. Lamont, 2007, The earnings announcement premium and trading volume, *NBER working paper*.
- Ginglinger, Edith, and Jacques Hamon, 2007, Actual share repurchases, timing and liquidity, *Journal of Banking & Finance* 31, 915–938.
- Graham, John R., and Campbell R. Harvey, 2001, The theory and practice of corporate finance: Evidence from the field, *Journal of Financial Economics* 60, 187–243.
- Grullon, Gustavo, and David L. Ikenberry, 2000, What do we know about stock repurchases?, *Journal of Applied Corporate Finance* 13, 31–51.
- Grullon, Gustavo, and Roni Michaely, 2004, The information content of share repurchase programs, *The Journal of Finance* 59, 651–680.
- Guant, Olivier, Jiang Pu, and Guillaume Royer, 2015, Accelerated share repurchase: pricing and execution strategy, *International Journal of Theoretical and Applied Finance* 18, 1550019.
- Howe, Keith M., Jia He, and G. Wenchao Kao, 1992, One-time cash flow announcements and free cash-flow theory: Share repurchases and special dividends, *The Journal of Finance* 47, 1963–1975.

- Hribar, Paul, Nicole Thorne Jenkins, and W. Bruce Johnson, 2006, Stock repurchases as an earnings management device, *Journal of Accounting and Economics* 41, 3–27.
- Ikenberry, David, Josef Lakonishok, and Theo Vermaelen, 1995, Market underreaction to open market share repurchases, *Journal of Financial Economics* 39, 181–208.
- Jensen, M., 1986, Agency costs of free cash flow, corporate finance, and takeovers, *The American Economic Review*.
- Lakonishok, Josef, and Theo Vermaelen, 1990, Anomalous price behavior around repurchase tender offers, *The Journal of Finance* 45, 455–477.
- Lang, Larry HP, and Robert H. Litzenberger, 1989, Dividend announcements: Cash flow signalling vs. free cash flow hypothesis?, *Journal of Financial Economics* 24, 181–191.
- Lee, D. Scott, Wayne H. Mikkelsen, and M. Megan Partch, 1992, Managers' trading around stock repurchases, *The Journal of Finance* 47, 1947–1962.
- Lintner, John, 1956, Distribution of incomes of corporations among dividends, retained earnings, and taxes, *The American Economic Review* 46, 97–113.
- Loughran, Tim, and Jay R. Ritter, 1995, The new issues puzzle, *The Journal of Finance* 50, 23–51.
- Manconi, Alberto, Urs Peyer, and Theo Vermaelen, 2015, Buybacks around the world, .
- Mitchell, Mark L., and Erik Stafford, 2000, Managerial decisions and long-term stock price performance, *The Journal of Business* 73, 287–329.
- Novy-Marx, Robert, and Mihail Velikov, 2016, A taxonomy of anomalies and their trading costs, *Review of Financial Studies* 29, 104–147.
- Peters, Ryan H., and Lucian A. Taylor, 2017, Intangible capital and the investment-q relation, *Journal of Financial Economics* 123, 251–272.
- Peyer, Urs, and Theo Vermaelen, 2009, The nature and persistence of buyback anomalies, *Review of Financial Studies* 22, 1693–1745.
- Pontiff, Jeffrey, and Artemiza Woodgate, 2008, Share issuance and cross-sectional returns, *The Journal of Finance* 63, 921–945.
- Poterba, James M., and Lawrence H. Summers, 1995, A ceo survey of us companies' time horizons and hurdle rates, *Sloan Management Review* 37, 43.
- Ritter, Jay R., 1991, The long-run performance of initial public offerings, *The Journal of Finance* 46, 3–27.
- Skinner, Douglas J., 2008, The evolving relation between earnings, dividends, and stock repurchases, *Journal of Financial Economics* 87, 582–609.

- Stephens, Clifford P., and Michael S. Weisbach, 1998, Actual share reacquisitions in open-market repurchase programs, *The Journal of Finance* 53, 313–333.
- Tsetsekos, George P., Daniel J. Kaufman Jr, and Lawrence J. Gitman, 1991, A survey of stock repurchase motivations and practices of major us corporations, *Journal of Applied Business Research (JABR)* 7, 15–21.
- Vermaelen, Theo, 1981, Common stock repurchases and market signalling: An empirical study, *Journal of Financial Economics* 9, 139–183.
- Wang, Chuan-San . S., Norman Strong, Samuel Tung, and Steve Lin, 2009, Share repurchases, the clustering problem, and the free cash flow hypothesis, *Financial Management* 38, 487–505.
- Wansley, James W., William R. Lane, and Salil Sarkar, 1989, Managements' view on share repurchase and tender offer premiums, *Financial Management* pp. 97–110.

Appendix A

Technical Details

A.1 Parser Overview

To extract the monthly data repurchase data from 10-Qs and 10-Ks filed on Edgar, I first download summaries listing all Edgar filings in a quarter and automatically scan these files for 10-Q, 10-K entries. A program (utilizing Apache Commons FTPClient) then downloads the over a terabyte of 10-Q and 10-K filings from Edgar to Amazon Web Services S3 storage. The parser runs in an Amazon EC2 instance, launching multiple threads that retrieve the files from S3 storage, parses the HTML (embedded in the filing) with JSoap and extract every single HTML table. Features are constructed for each HTML table using a variety of methods, including regular expressions and the structure of the HTML. The features define a vector in a high-dimensional feature space and if the vector occupies a particular region of the space, the table is considered a table denoting share repurchases by the company. Regular expressions are used to extract dates, to identify labels of the columns, to identify text denoting units (eg. "millions of shares", "(thou)" etc...), and other key data. Text from nearby columns is then used to identify what various numbers in columns denote (eg. is 2,523 the number of shares purchased, the authorized total remaining, or the price paid?). The final result is a row of data for each month with a share repurchase, and these rows are sent to

Postgresql database on Amazon Relational Database Services (RDS).

As mentioned before in the data section, all this data can be aggregated at the quarter level and then rigorously checked for consistency with Compustat. The finest resolution of Compustat is units of 1,000 shares, and I consider my share count to match Compustat if the absolute error is within 2,000 shares or the percent error is within 2%. I consider the average price paid over the quarter to match Compustat if the error relative to the Compustat value is within 2%. It appears Compustat pulls values off the total line, and expecting an exact match is not reasonable due to rounding.

A.2 Matching to other data sets

I first match my SEC filings to the list of filings in WRDS SEC Analytics suite to find the first date the filing appeared on EDGAR (this is almost always the same as the filing date listed on the SEC filing itself). Matching to WRDS sec forms table also gives the Compustat GVKEY, allowing matching with Compustat data. To get the dates correct, I match the Compustat variable APDEDATEQ, the actual period end date, with the SEC filing's conformed period of report. This matching method is problematic for old data, but works extremely well for data since 2004 (which is where my sample is). The data is then matched to CRSP using the CRSP / Compustat link table file ccm.ccmxpf_lnkhist after I purge duplicates. Cusips are taken from the CRSP daily stock events file and then I match with IBES or other data that utilizes cusip.

A.3 Duplicates

A significant issue is duplicates and one to many matches: multiple 10-Q, 10-K filings for the same conforming period (eg. due to restatements or changes of fiscal year), the same repurchase data reported in later filings, multiple CIKs referring to basically the same parent company, etc... I

apply rigorous logic throughout my code to eliminate duplicates. Some general principles I follow are that monthly data is pulled only from filing for the quarter the month is in (eg. if repurchases for January 2008 is described in multiple filings, I use the value from the Q1 2008 filing if the fiscal year end is in December) and in the case of multiple filings covering a period (eg. with a fiscal year change), the first filing is used.

A.4 Abnormal returns: characteristic adjusted returns

Company characteristics (market equity, book to market equity, etc...) are calculated from the Compustat annual file using the same basic methods as utilized by Fama and French and described on Ken French's website. A company's characteristics are translated to percentiles/breakpoints using the Fama-French files showing percentiles breakpoints for the NYSE, and then these are used to find a matching Fama-French portfolio (eg. book to market equity, market equity to operating profitability etc...). Portfolios are assigned using the same lagged annual Compustat data as in Fama-French.

Book equity is calculated with the SQL code "seq - COALESCE(pstk, 0) + COALESCE(txdtc, 0) as be." Operating profit is calculated as "(revt - cogs - COALESCE(tie,0) - COALESCE(xsga,0)) as op_numerator." Market equity is calculated as "csho * prcc_f as me."

A.5 Abnormal returns: risk based models

I calculate market model, Fama-French three factor, and Fama-French five factor betas using monthly data and a rolling window from 30 months to 6 months prior to the date in question. Even though I'm interested in daily abnormal returns, estimating the betas naively on a daily data is almost certainly inappropriate. A fact well known since at least the 1980s is that small stocks tend to have *higher* than average betas (i.e. > 1) using monthly data while *lower* than average

betas using daily data! Consequently, applying the Fama-French three factor model on daily data of smaller stocks leads to implausibly low beta estimates and implausibly high estimates of alphas (the missing loading on RMRF in a sense shows up as α). With betas estimated on daily data, you get non-sensical, high abnormal returns for everything, almost no matter what you do. Rather than building a complicated model to account for lagged effects, I use the betas estimated from monthly regressions and apply them daily data to calculate daily abnormal returns. This yields unconditional average daily abnormal returns in the larger CRSP universe that are remarkably close to zero, even closer to zero than the characteristic adjusted portfolio abnormal returns.

To efficiently compute the rolling window estimate of betas I perform rank one updates of the design matrix using LAPACK's `dgemm`, then form the LU factorization from `dgetrf` routine and solve the system with `dgetrs`.

A.6 Accurate average price data

A huge concern is that the average price paid in a quarter may be incorrect. The following checks are applied:

- No red-flag, parse errors were detected.
- No share splits in the prior 120 days. A share split is in some sense a change of units: a 12 for 1 split is like changing from feet to inches. There is a significant problem though in determining automatically what units the 10-Q, 10-K table I parse is reported in! For example, imagine a share split occurs in the week *after* a 10-Q is filed or perhaps between the close of the quarter and the filing date. In these cases, 10-Qs sometime report transaction prices in the new units and sometimes they use the earlier units. It isn't consistent across firms and time. And the use of the Compustat cumulative adjustment factor $ADJEX_F$ doesn't fully resolve the problem (it tells you what units to use for Compustat data, not this particular table in the raw filing, and the two don't perfectly coincide). This does have a potential

to introduce overall bias if the decision to split shares is based upon recent stock market performance, but this bias is much less than including erroneous 100% returns! (If the filing reflects a 2 for 1 stock split, the average price reported would be half the CRSP price of the period.) Greater sophistication is possible here, but it's a non-trivial problem that cannot be trivially solved using Compustat or CRSP cumulative adjustment factors.

- The filing does not refer to an accelerated share repurchase program. In the case of an accelerated share repurchase program, the transaction price reported and the timing don't have the same meaning as in open-market repurchases.
- The shares purchased pursuant to a public program is the same as the overall number of shares purchased (i.e. exclude cases where the average price may reflect employees forfeiting unvested shares and the company acquiring them at a price of perhaps 0.01 per share).
- Dual class share companies are excluded. For example Comcast has multiple classes of common stock, they say they repurchase whatever is cheaper, and my software can't tell from the filing which one they're repurchasing (hence I don't know what CRSP permno to compare to).
- The currency in the filing is in US dollars. Eg. a company that reports share prices in Canadian dollars in their filing would introduce additional, unnecessary currency issues.
- No distributions during the period. If a dividend occurs within a month, I have no way of telling whether the transaction occurred before the ex-dividend date or on or after the ex-dividend date.
- The length of the period is between 20 and 40 days. I'm only looking for monthly data.
- The average price paid by the firm is within the trading range over the period based upon CRSP data. This excludes some additional cases where the repurchase price is some residual

artifact of other transactions: eg. the shares were acquired by the firm when outside investors exercised puts sold by the firm on its own shares.