NEW METHODS IN EMPIRICAL FINANCE

A Dissertation

by

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ABSTRACT

This dissertation studies two new methods in empirical finance. Section 2 applies a rolling estimation window approach to adjust for time-varying risk parameters in asset pricing models when estimating long-run abnormal returns after major corporate events. Abnormal returns are defined as realized returns minus predicted returns on each day in a five-year, post-event period. A variety of asset pricing models are employed to compute out-of-sample predicted returns in different estimation windows for seasoned equity offerings (SEOs) and mergers and acquisitions (M&As). We find that, after an initial significant return response in the month or two after corporate announcements, abnormal returns thereafter disappear. Robustness checks corroborate our results: (1) with or without matched and random control samples, (2) for different asset pricing models including the CAPM market model, and (3) in robustness tests of share repurchases (SRs), stock splits (SPLTs) as well as different subperiods. Also, simulation tests confirm the robustness of the RPE method to potential risk shifts. In summary, after dynamic risk adjustment, long-run abnormal returns are not evident after these major corporate actions.

Section 3 proposes a new empirical method to estimate the global minimum variance portfolio without the covariance matrix to avoid associated estimation errors. Unlike previous studies, we employ extant asset pricing models to test efficiency, sort portfolios, and assign weights to individual assets. Based on out-of-sample analyses of U.S. stock returns in the sample period from 1968 to 2019, empirical results show that the global minimum variance portfolio has relatively high expected returns, low variance, and high Sharpe ratios. The results are robust with respect to different asset pricing models, extreme weights for individual stocks, and different subperiods.

DEDICATION

To my parents and my beloved wife Yudi.

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1. INTRODUCTION

There are lots of unexplored areas and questions in the finance area. Instead of providing evidence for a specific question, this dissertation focuses on improving the associated methodologies that could be not only used here but applied in more future researches.

In this dissertation, we propose two new methods that could be used in empirical finance studies. People have been using event study methods in the last several decades, during which the short-run method has been proven to be robust. However, the long-run method is still subject to many questions. We apply the short-run method into the long-run study in Section 2 of this dissertation, allowing risks to be adjusted dynamically. In the next section, we develop a new method, attempting to empirically estimate the global minimum variance portfolios while avoiding the estimation errors from the covariance matrix. Instead of using a complex mathematic calculation to estimate the covariance matrix, we use only asset pricing models to test efficiency, sort portfolios and assign weights to individual assets.

In Section 2, we run the long-run event study tests while adjusting risk changes on a daily basis. Traditional long-run event study methods assume that firms have a constant risk level after major corporate events such as seasoned equity offering (SEOs) and mergers and acquisitions (M&As). However, either capital structure change or getting into another business could result in a risk change. Such a change will affect the results of event study (see Eckbo, Masulis, and Norli (2000), Gompers (2015), and Baker (2016)). We apply the robust short-run event study method into the long-run analysis, with abnormal returns defined as daily realized returns minus the predicted returns. Adapting the conditional CAPM framework, we recalculate the predicted return using the most updated information every day. Using such an RPE method, we re-investigate whether the long-run abnormal returns exist after major corporate events.

Empirical results show that short-run abnormal returns exist but not in the long term. Results are consistent for SEOs, M&As, share repurchases (SRs), and stock splits (SPLTs). The RPE method is also robust to different asset pricing models, different (or without) control groups, and different sub-periods. Results contribute to the controversial question about market efficiency. Simulation tests using real SEOs data show that the RPE method controls both types of errors in a reasonable range, even when risk is shifting. We conclude that no long-run abnormal returns are associated with major corporate events and suggest future use of the RPE method in long-run event study researches.

In Section 3, we propose a new method to estimate the global minimum variance portfolios empirically. Traditional methods highly depend on the estimation of the covariance matrix between composition assets. Even with the most updated techniques, such estimation processes are still heavily affected by estimation errors. We propose that estimation errors mainly affect expected returns of the minimum variance portfolio. Other empirical results show that the portfolio does not consistently beat a simple equal-weighting strategy (see DeMiguel, Garlappi, and Uppal (2009b)). To avoid such errors, we develop a new method, using individual stocks' idiosyncratic risk exposures to sort and assign weights. The idiosyncratic risk exposure is estimated as the variance of residual terms from the regression between excess returns and asset pricing models.

As we expect, the global minimum variance portfolio estimated using the new method has a relatively low out-of-sample variance (about half compared to the value-weighted market portfolio). Combined with a high expected return, the portfolio has a more than 100% increase from the market portfolio in terms of the Sharpe ratio. In addition, the results are robust with respect to different asset pricing models, extreme individual weights, and transaction costs. The results confirm the success in estimating the global minimum portfolio using the new method.

2. DYNAMIC RISK ADJUSTMENT IN LONG-RUN EVENT STUDY TESTS

2.1 Introduction

A large and growing literature exists on the controversial issue of long-run abnormal returns. Many studies find significant long-run abnormal returns after major corporate actions, including initial public offerings (IPOs), seasoned equity offerings (SEOs), mergers and acquisitions (M&As), dividend initiations, stock repurchases, among others.[1] By contrast, other studies find little or no evidence of long-run abnormal returns.[2] The controversy centers in large part on the question of market efficiency. In an efficient market, according to Fama (1998), long-run abnormal returns should not persist over time due to arbitrage activities by investors continuously adjusting returns for their risks. On the other hand, market inefficiency can exist under a variety of conditions based on the psychological (behavioral) responses of market investors.[3]

Intuitively, most major corporate events will change the risk of a firm. An SEO, IPO, or stock repurchase will changes the firm's capital structure and associated financial risk. M&As allow firm to diversify into different industries or expand their current business activities. Even a small event-induced variance could affect event study results (e.g., see Boehmer et al. (1991)). In an efficient market, dynamic risk adjustment is crucial to accurately measure abnormal returns coincident with corporate events over an extended period of time. To continuously adjust for risk, previous long-run event studies using buy-and-hold abnormal returns (BHARs) (e.g. see Ikenberry, Lakonishok, and Vermaelen (1995) and Barber and Lyon (1997)) and calendar time abnormal returns (CTARs) (e.g., see Ibbotson (1975) Kothari and Warner (2007)) typically subtract matched control stocks'

[1]See studies by Ibbotson (1975), Asquith (1983), Ritter (1991), Agrawal, Jaffe, and Mandelker (1992), Loughran and Ritter (1995), Michaely, Thaler, and Womack (1995), Spiess and Affleck-Graves (1995), Brav, Geczy, and Gompers (2000), Eckbo and Norli (2005), Mitchell and Stafford (2000), Lyandres, Sun, and Zhang (2008), Billett, Flannery, and Garfinkel (2011), How, Ngo, and Verhoeven (2011), Evgeniou, de Fortuny, Nassuphis, and Vermaelen (2018), Huang and Ritter (2020), Malmendier, Moretti, and Peters (2018), Kolari, Pynnonen, and Tuncez (2021), and others.

[2]For example, see Brav and Gompers (1997), Eckbo, Masulis, and Norli (2000), Loughran and Vijh (1997), Brav (2000), Eckbo, Masulis, and Norli (2007), Boehme and Sorescu (2002), Byun and Rozeff (2003), Gompers and Lerner (2003), Bessembinder and Zhang (2013), Lee, Strong, and Zhu (2014), Fu and Huang (2015), Caton, Goh, Lee, and Linn (2016), Bessembinder, Cooper, and Zhang (2019), and others.

[3]See behavioral theories by Kahneman and Tversky (1982), De Bondt and Thaler (1985), Jegadeesh and Titman (1993), Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and others.

returns from event study stocks' returns. Matched control stocks have similar size and book-to-market ratios (for example) as event stocks.

Recent work by Bessembinder and Zhang (2013) and Bessembinder, Cooper, and Zhang (2019) suggests that simple, matched-control risk adjustments in previous studies are insufficient and that a wide variety of firm characteristics should be taken into account to more fully account for risk. Eckbo, Masulis, and Norli (2000) argues that underperformance for SEOs could be explained by a proper control for risk. Alternatively, in legal event studies, researchers recommend rolling estimation period windows to allow time-varying risk parameters in asset pricing models' estimation of abnormal returns. For example, Gompers (2015) estimates the daily returns of Barclays shares as a function of market returns in the CAPM market model (see Sharpe (1963), Sharpe (1964), and Fama (1968)) using a rolling estimation window of 252 trading days. Incrementing the estimation period forward one day at a time from 2007 to 2012, he finds that the regression coefficients change over time. Subsequent abnormal return analyses test for significant one-day-ahead prediction errors (viz., realized minus predicted returns) for Barclays on a daily basis in the sample period. Another paper by Baker (2016) proposes rolling estimation windows in legal cases that utilize event study evidence. He employs a rolling 250-day window just prior to the one-day-ahead estimation of abnormal returns using the CAPM market model. Based on 29 large U.S. firms, empirical tests of their stock returns in different sample periods indicate that this rolling approach reduced rejection frequencies (i.e., Type I errors) compared to an in-sample estimation procedure (see also Sehgal, Banerjee, and Deisting (2012)). While there is precedent in legal studies for a rolling prediction error (hereafter RPE) approach to dynamic risk adjustment, this approach has not been applied to long-run event studies of major corporate events in the finance literature to our knowledge.

In this paper we fill the aforementioned gap in the event study literature by investigating long-run abnormal returns after major corporate actions based on the rolling prediction error (RPE) approach for estimating abnormal returns. Starting with event day 0 of a corporate announcement, we estimate a variety of asset pricing models both before and after the event day. Abnormal returns for each event stock are computed on day 0 as its realized return minus predicted return (i.e., based on the alpha and beta parameters of the model in the out-of-sample estimation window). This process is rolled forward one day at a time over the five-year, post-event period (i.e., event days T = 0, ..., L) to generate a daily time series of abnormal returns. As the process is rolled forward day by day, model risk parameters are allowed to vary over time and dynamically adjust for changes in their risk levels.[4] Our method follows Fama and French (2020) using time varying factors and the conditional CAPM test proposed by Lewellen and Nagel (2006). In this respect, our short-run analyses produce unbiased true conditional alpha and beta estimates assuming their stability in the event day. Although the conditional asset pricing model does not fully fix the unconditional model, long-run event study conditioning is implemented using the most updated information consistent with the efficient market hypothesis. Following Boehme and Sorescu (2002), to further adjust for risk, we also compute abnormal returns as the difference between the daily abnormal returns of event stocks and those of a matched control group of stocks. Additional tests substitute a random sample of nonevent stocks for the control group. Empirical analyses are performed for large samples of SEOs and M&As.

In preliminary tests, we find that, as the estimation window for different models is shortened before events, abnormal returns noticeably decrease. Also, measured abnormal return patterns differ markedly when the estimation window is before as opposed to after events. Consistent with these findings, formal tests reveal that market beta significantly shifts after events. To better adjust for shifting risk, we subsequently use an estimation window that straddles each event day (viz., combining two months before and after events). Using this approach, we detect abnormal returns in the month or two after events but not thereafter over a five-year, post-event period. Thus, our results suggest that short-run abnormal returns exist but not long-run abnormal returns. These findings are confirmed: (1) with or without matched and random control samples, (2) for different asset pricing models including the CAPM, and (3) in robustness tests of share repurchases (SRs),

[4] Nonsynchronous trading could be a issue using daily data as mentioned by Scholes and Williams (1977) and Dimson (1979). However, Brown and Warner (1985) have shown that short-term event study methods are robust using daily data. We repeated our tests with Dimson aggregated coefficients and the results are unchanged. Methodology details and results are reported in appendix.

stock splits (SPLTs) as well as different subperiods. We conclude that, after dynamic adjustment of risk parameters in asset pricing models, no long-run abnormal returns are evident. By implication, consistent with Fama (1998)'s conjecture, investors efficiently price risk in the market and appropriately adjust expected returns over time.

To better understand the effects of risk shifts, we conducted simulation analyses using real SEO data and the CAPM market model. Results for the RPE method show that both Type I and II errors are controlled within a reasonable range for plausible risk shift scenarios. However, the traditional CTAR method has a high chance of falsely rejecting zero abnormal returns when risk is shifting. Results are consistent with different levels of risk change and true abnormal returns. We conclude that the RPE method is robust to risk shifts in measuring and testing long-run abnormal returns.

The next part reviews our data. Section 2.3 explains methods, Section 2.4 reports the empirical results, and last Section 2.5 concludes.

2.2 Data and Sample Selection

Samples of seasoned equity offerings (SEOs), mergers and acquisitions (M&As), stock repurchases (SRs), and stock splits (SPLTs) are gathered for the period 1980 to 2015 (i.e., long-run event study analyses extend over a five-year, post-event period). The SEO sample consists of observations downloaded from the Thomson ONE (SDC) database. We drop Global Depository Receipts, American Depository Receipts and unit offerings, and utility and financial firms. As in Betton, Eckbo, and Thorburn (2008), we screen for M&A events recorded as: (1) a merger (M), majority interest (AM), remaining interest (AR), or partial interest (AP); and (2) control bids with 50% or more of the target held by the acquirer. Small deals are dropped by selecting those with transaction values exceeding $5 million and relative size in excess of 5%. As a robustness check in later analyses, we gather other samples of U.S. share repurchases (SRs) and stock splits (SPLTs). SPLTs events are downloaded from CRSP database with distribution codes 5,523 and 5,533. In an initial sample screen, we retain only the first SR and SPLT in a given year.

An issue arises for firms with multiple events within five years. In this case an abnormal return for a firm could be (for example) in both post-event year two and post-event year five depending on which event is used. To avoid duplicate firms in our analyses, we drop overlapping SEOs, M&As, SRs, and SPLTs in the five-year period after an event. This screen results in the following final (total) samples: 2,978 (7,327) SEOs, 2,886 (16,391) M&As, 4,188 (16,391) SRs, and 2455 (4602) SPLTs.

We employ two groups of control firms. First, matched controls for SEOs, M&As, SRs, and SPLTs are constructed based on size and book-to-market ratio (BM) characteristics on CRSP and Compustat. Market capitalization (firm size) is measured in December prior to these events. As in Fama and French (1993), book equity is the Compustat book value of stockholders equity, plus balance sheet deferred taxes and investment tax credits (if available), minus the book value of preferred stock. Like Eckbo, Masulis, and Norli (2007) and Bessembinder and Zhang (2013), we match event firms to control firms using the closest BM among firms with market capitalization between 70% and 130% of the event firm. Matching firms that are in the sample of acquirers within ten years around an event date are dropped. Second, random controls for event firms are constructed by blindly selecting an equal number of nonevent firms from CRSP database common stocks.

Table B.1 shows the number of corporate events in different years. The total samples are shown in parentheses next to the final sample after dropping overlapping events in the five-year, post-event period. It is notable that events appear to cluster over time to some extent with greater numbers of SEOs, M&As, and SRs in the 1990s.

2.3 Research Methodology

2.3.1 Rolling Prediction Error (RPE) Approach

Early short-run event studies apply the CAPM market model of Sharpe (1963), Sharpe (1964), and Fama (1968), which can be specified as follows for the excess return on the ith common stock:[5]

$$R_{it} - R_{ft} = \alpha_i + b_i(R_{mt} - R_{ft}) + e_{it}, \tag{2.1}$$

[5] See also Campbell, Lo, and MacKinlay (1997).

where R_{mt} is the daily return on the value-weighted market index, R_{ft} is the daily return on one-month U.S. Treasury bills, and e_{it} is a white noise error term. Most authors estimate a time series ordinary least squares (OLS) regression with stock returns before a relatively short event window containing the event announcement day (day 0).[6] For example, a period of one year before an 11-day event window could be used to estimate the market model (i.e., five days before and after day 0). Following conventional practice established by Fama, Fisher, Jensen, and Roll (1969), abnormal returns are estimated for each day in the event window (e.g., $T = 1, ..., L = 11$) as the daily forecast error:

$$AR_{iT} = [R_{iT} - R_{fT}] - [\hat{\alpha}_i + \hat{b}_i(R_{mT} - R_{fT})]. \tag{2.2}$$

According to Pynnonen (2005), given that α_i and b_i have estimation error, the true market model can be written as:

$$[R_{iT} - R_{fT}] = \alpha_i + \gamma_{iT} + b_i(R_{mT} - R_{fT}) + e_{iT}, \tag{2.3}$$

where γ_{iT} captures true return effects due to the event on day T. Substituting this expression into equation (2) and rearranging terms, we have:

$$\hat{AR}_{iT} = (\alpha_i - \hat{\alpha}_i) + (b_i - \hat{b}_i)(R_{mT} - R_{fT}) + \gamma_{iT} + e_{iT} \tag{2.4}$$

Because $E[\hat{\alpha}_i] = \alpha_i$ and $E[\hat{b}_i] = b_i$ in OLS estimation of the CAPM market model, the expected abnormal return can be defined as:

$$E[\hat{AR}_{iT}|[R_{mT} - R_{fT}]] = \gamma_{iT}. \tag{2.5}$$

This abnormal return (i.e, prediction error) can be averaged across N sample firms. Also, by compounding abnormal returns AR_{iT} within the event window, cumulative abnormal returns (CAR_{iT}) for the ith stock can be computed as well as their cross-sectional average on event day T for all event stocks (CAR_T).

[6] See for example Dodd and Ruback (1977) and Eckbo (1983).

In this paper, following previously cited legal studies, we employ the above short-run event study framework to compute rolling prediction errors (RPEs) as estimates of long-run abnormal returns. To do this, each day in the five-year, post-event window is treated as a separate event day. We begin by estimating the market model using daily returns for one year (for example) prior to day 0 and compute AR_{i0} after this estimation window on day 0. Next, the entire process is rolled forward one day to estimate another market model and compute AR_{i1} on day 1. Rolling forward one day at a time in a five-year, post-event window ($T = 0, ..., L$), we create the daily time series $AR_{i0}...AR_{iL}$ beginning with the event announcement on day 0 and ending on the last day of the five-year, post-event period denoted day L.

Because the beta risk parameter ($\hat{b}_i$) can change over time, we also estimate the market model using 6-, 3-, and 2-month estimation periods prior to day T. As the estimation period is shortened, beta parameter estimates become more closely associated with the event. As mentioned in the previous section, it is likely that major corporate actions affect not only returns but risks of stocks. Of course, even a 2-month estimation period contains lagged risk information, which means that dynamic risk changes are not fully captured in abnormal returns. Some researchers point out that risk parameters estimated in the days just prior to day 0 are biased. For this reason, Salinger (1992) recommends using a post-event estimation window. Following this logic, we also estimate the market model using daily returns in the two months *after* day T to compute AR_{iT}. This approach allows for risk shifts after the event. Additionally, to mitigate the effects of risk shifts on the estimation of abnormal returns, some authors estimate the market model with stock returns both before and after the event window containing the event announcement day 0 (e.g., see Dodd and Ruback (1977) and Eckbo (1983)). Using this straddled estimation window approach, we combine the two months before and two months after each event day T to estimate the market model.

The use of an estimation period that straddles event days enables formal tests for risk shifts. To do this, dummy variables are incorporated in the CAPM market model to capture potential shifts in alpha and beta estimates around the abnormal return day as follows:[7]

$$(R_{it} - R_{ft}) = \hat{\alpha}_i + \hat{\alpha}'_i D_{it} + \hat{b}_i(R_{mt} - R_{ft}) + \hat{b}'_i D_{it}(R_{mt} - R_{ft}) + e_{it}, \qquad (2.6)$$

where D_{it} equals 0 in pre-event-days and 1 in post-event-days. In forthcoming analyses we test for risk shifts using different pre- and post-event estimation windows. If the mean coefficient $\bar{\hat{b}}'_i$ does not equal zero, we infer that average beta risk shifted among the sample stocks after the event.

2.3.2 BHAR and CTAR Approaches

As discussed earlier, long-run event studies commonly measure and test the post-event effects of corporate actions by means of buy-and-hold abnormal returns (BHARs) and calendar time abnormal returns (CTARs). BHARs are defined over holding period $(1, h)$ for h months as follows:

$$\texttt{BHAR}_i(h) = \prod_{t=1}^{h}(1 + R_{it}) - \prod_{t=1}^{h}(1 + R^c_{it}), \qquad (2.7)$$

where R_{it} and R^c_{it} are returns for the event stock and a control stock, respectively.[8] BHAR has the advantage of capturing the representative investor experience.

Seminal work by Ibbotson (1975) introduced the calendar time abnormal return (CTAR) approach. He examines the long-run performance of newly issued common stocks over 60 months using a market model wherein the intercept α_i term measures abnormal performance. Using this Jensen (1968)'s alpha approach, his findings indicate underpricing of new issue offerings in addition to declining systematic risk over time as issues become seasoned. Boehme and Sorescu (2002) propose an adjusted CTAR approach that creates a hedge (zero-investment) calendar time portfolio with long positions in event sample stocks and short positions in matched control stocks. The latter control stocks are intended to help mitigate unknown common risk factors. However, an implicit assumption is that the matching firm is the same as the event firm. Numerous studies have shown that event firms differ on various dimensions including both risks and firm characteristics

[7]For example, see Dodd and Ruback (1977).

[8]We obtain monthly returns from the CRSP database for U.S. common stocks.

(e.g., Grullon, Michaely, and Swaminathan (2002), Carlson, Fisher, and Giammarino (2006), Li, Livdan, and Zhang (2009), Bessembinder and Zhang (2013), Bessembinder, Cooper, and Zhang (2019), and others). Hence, it is unclear how to form matched controls. In forthcoming analyses we follow previous researchers (e.g., Ritter (1991), Lyon, Barber, and Tsai (1999), and others) by using size/book-to-market matched controls but also utilize a random sample control group. Results for these differerenced abnormal returns are compared to results without any control sample. As we will see, our RPE approach generates similar abnormal return findings with or without control samples. As such, the construction of appropriate control samples is not necessary in the RPE approach.

We provide CTAR results based on an adjusted Fama and French (2015) and Fama and French (2018) five-factor model augmented with the momentum factor. Monthly portfolio return differences between each event stock and either its matched control stock or random control stock are regressed on monthly multifactors as follows:

$$(R_{it} - R^c_{it})_{pt} = \alpha_p + \beta_p(R_{mt} - R_{ft}) + s_p SMB_t + \\ h_p HML_t + r_p RMW_t + c_p CMA_t + m_p MOM_t + e_{pt}, \quad (2.8)$$

where α_p defines the abnormal return denoted CTAR, $(R_{it} - R^c_{it})_{pt}$ is the monthly, equal-weighted portfolio return difference between the simple returns of each event stock and its control stock, MOM is the momentum factor, and other notation is as before. In month t the portfolio return $(R_{it} - R^c_{it})_{pt}$ takes into account all stocks whose event period contains the month. In this test method, the number of stocks in month t (N_t), can vary monthly from zero to the total number of sample stocks N (i.e., if $N_t = 0$, the month is dropped). In general, CTAR reflects the risk-adjusted average monthly abnormal return of event stocks.

2.3.3 Potential Biases in Long-Run Abnormal Returns

A variety of problems are inherent in the estimation of long-run abnormal returns. For example, according to Fama (1968) and Mitchell and Stafford (2000), the BHAR approach is biased by cross-sectional correlation among event stocks' abnormal returns. This issue is eliminated in the CTAR approach by time series portfolio returns, which include cross-correlations of abnormal returns (see Lyon, Barber, and Tsai (1999) and Mitchell and Stafford (2000)). Even so, as recognized by Loughran and Ritter (1995), CTAR sacrifices some power due to the formation of portfolios. Also, the $\hat{\alpha}_p$ intercept can embody missing factors excluded from an asset pricing model. With respect to the latter issue, using the adjusted CTAR approach of Boehme and Sorescu (2002) helps to zap out this potential bias to the extent that missing factors' information is contained in both event stocks and differenced controls. If this is so, a random sample of control stocks should eliminate bias from missing factors also. In forthcoming analyses, we use both matched and random samples as controls in the adjusted CTAR model approach.

Loughran and Ritter (2000) cite three reasons that CTAR analyses can have low power to detect abnormal returns, including event-date clustering, the likelihood of greater misvaluations among small compared to big firms, and possible benchmark contamination due the contemporaneous inclusion of event stock returns in the asset pricing factors. Also, they argue that behavioral timing is more likely in the case of managerial actions that affect cash flows than routine or other events. The intuition is that managers act in the shareholders' interest, especially among small firms prone to misvaluations. Consistent with their recommendation, we focus on anomalies associated with equity issues, mergers and acquisitions, share repurchases, and stock splits.

It is worthwhile to contrast our rolling prediction error (RPE) approach with the prominent CTAR approach. The focus of CTAR is the estimation of Jensen's alpha in a post-event period of one-to-five years in long-run event studies. This calendar-time-based approach assumes that the risk profile of an event firm does not significantly change over time. By not adjusting for dynamic changes in firm risk, a bad-model problem is possible. Fama (1998) argues that asset pricing models jointly test market efficiency and expected (normal) returns. Errors in expected returns due to inappropriate risk adjustment multiply as the return horizon increases in long-run event studies. In his words, "The bad-model problem is less serious in event studies that focus on short return windows (a few days) since daily expected returns are close to zero and so have little effect on estimates of unexpected (abnormal) returns. But the problem growswith the return horizon." (Fama (1998, p. 291)).

To mitigate bad-model problems, he recommends that firm-specific models should be used, such as the market model in short-run event studies. Model parameters are estimated outside of the event period and then employed to estimated expected returns in the event period conditional on market returns. In this regard, CTARs have the advantage of in-sample parameter estimates but impose constraints on the cross-section of average stock returns. Our proposed RPE approach to abnormal returns – that is, prediction errors in rolling one-day event windows – helps to reduce bad-model problems. Because it is estimated for each individual firm, firm-specific expected returns are measured, rather than cross-sectional average returns as in CTAR. Also, as opposed to calendar time, RPE is based on event time. All stocks' daily abnormal returns are tracked in a five-year, post-event period.

The RPE approach eliminates potential bias from event-date clustering but is exposed to potential correlation biases in t-tests of the daily post-event time series of abnormal returns. In this regard, autocorrelation is typically not a major issue. Even if some autocorrelation exists between adjacent returns, the correlations of distant returns decay exponentially to near zero. A 5% first order autocorrelation will result in a $0.05^2 = 0.0025$ second order autocorrelation. Following Kolari and Pynnonen (2010), in this case average correlation in a 10 day cumulative abnormal return would be around 0.01, which changes unadjusted t-statistics by only approximately $\sqrt{1 + (n-1) * 0.01} \approx 1.05$ or 5 percent. However, cross-sectional correlation is a greater concern. Given only a 5% correlation, the correction becomes $\sqrt{1 + (n-1) * 0.05} \approx 1.20$ or 20 percent, which can substantially changed the significance of t-statistics. Additionally, in the autocorrelation case the correction factor stays the same as n increases, but in the cross-correlation case this factor increases with n.[9] Implicitly this effect has been observed in some empirical studies (e.g., see Bessembinder and Zhang (2013)).

In our RPE method, although abnormal returns are tested based on event days, it is possible

[9] Mathematical proof is available upon request from the authors.

that different event days for two stocks are the same calendar date. To address this issue, standard errors are clustered based on calendar time to produce robust t-statistics. Overall, robust t-tests do not change our results. The t-statistics decrease to some extent, but significant results remain significant after robustification (albeit at a somewhat lower significance level in some cases). For these reasons, all tables report cross-correlation robust t-statistics.

Another approach to reducing bad-model problems is to more comprehensively control for firm characteristics. Bessembinder and Zhang (2013) regress differences in the stock returns of event stocks and matched control stocks on a variety of firm characteristics and market risk factors. Also, a closely related paper by Bessembinder, Cooper, and Zhang (2019) adjusts event stock returns for 14 firm characteristics. A relatively short three-month post-event window is used to maintain these characteristics in benchmarking abnormal returns. They find that firm characteristics do a good job of explaining post-event returns. In both of these studies, abnormal returns are generally not detected after a number of major corporate events. Of course, controlling numerous firm-specific characteristics over a long event horizon extending from one-to-five years is difficult to implement and raises questions about which characteristics need to be controlled. Also, firm characteristics tend to be highly correlated that rendering reliable inference about an individual characteristic's true effect. By contrast, our RPE approach is relatively simple to execute with stock market information, thus bypassing the need for gathering large amounts of firm-level accounting information which itself introduces considerable ambiguity in terms of the selection of accounting variables.

2.4 Empirical Results

In this section we report the results of abnormal returns estimated using the proposed RPE approach for SEOs and M&As. Daily abnormal returns are averaged in post-event periods and then scaled up to average monthly returns. Robustness checks are provided for share repurchases (SRs), stock splits (SPLTs) as well as different subperiods. Also, we document comparative results based on traditional BHAR and CTAR approaches for estimating long-run abnormal returns.

2.4.1 RPE Results

We begin with matched control RPE results for SEOs and M&As. For ease of exposition, Tables B.2 and B.3 report results for the five-factor plus momentum model, and those for the market model and five-factor model are provided as well for comparative purposes. Different estimation windows relative to event days are used: 1 year before, 3 months before, 2 months before, and 2 months after. Post-event average abnormal results are broken down by event stocks (Panel A), matched control stocks (Panel B), event stocks minus matched control stocks (Panels C and D with yearly and quarterly abnormal returns, respectively).

Referring to Panel C of Table B.2 with average abnormal returns computed as SEOs minus matched controls in the 1 year post-event period, abnormal returns of -1.69 percent are significant with $t = -10.97$ using a 1 year before estimation window but are only -0.05 percent with insignificant $t = -0.25$ using the 2 months before estimation window. In other post-event years 2 to 5, no t-statistics are significant in Panel C. Using 2 months after estimation window, Panel C reports a positive abnormal return that is marginally significant with t-statistic equal to 2.13 in the first year. It is mainly driven by a positive abnormal return with significant t-statistic of 3.12 in quarter 1 after SEO offerings. In this panel, note that the sign of quarterly abnormal returns switches from negative to positive using 1 year before versus 2 months after estimation periods.

Similar abnormal return patterns for M&As are apparent in Table B.3. In post-event year 1 abnormal return results in Panel C, the t-statistic is again negative and significant for the 1 year before estimation window, but now the t-statistics are negative and significant for both 3 month and 2 month before estimation windows. The quarterly results in Panel D suggest significant abnormal returns in all four quarters using a 1 year before estimation window but less significant abnormal returns using other estimation windows. Also, using a 2 month after estimation window, not only are the abnormal returns generally insignificant but again become predominantly positive rather than negative using pre-event estimation windows.

Summarizing these preliminary findings, the estimation window used to compute model parameters substantially affects both the sign and significance of long-run abnormal returns after

SEO and M&A events. As estimation windows shorten, abnormal returns tend to decrease in magnitude and significance. These same patterns are evident in Appendix Tables B.12 to B.15 based on the market model and five-factor model, respectively. In this regard, it is interesting that the results are little changed across different models. The market model produces abnormal returns computed as event stocks minus matched controls that are similar to multifactor models using different estimation windows.

Over the five-year, post-event period, Figures C.1 and C.2 illustrate the daily cumulative abnormal returns (CARs) for SEOs and M&As, respectively, with matched controls and different estimation windows. Comparing the results in Panels A, B, and C in these figures, it is clear that abnormal returns decrease as the estimation window before SEO and M&A events decreases. Notice that, in Panel C using a 2 month before estimation window, CARs initially decline for a few quarters but then return to zero by the end of the 5-year post-event period. Conversely, in Panel D using a 2 month after estimation window, CARs initially increase, then level off, and later increase at the end of the five-year, post-event period (i.e., reaching about 4 percent). The CAR patterns for M&As in Panels C and D of Figure C.2 are somewhat different from SEOs. In Panel C we see that abnormal returns are again negative over a few quarters but then reach a minimum and flatten out for the most part. And, in Panel D abnormal returns increase after M&A announcements but continue to increase throughout the five-year, post-event period. These results confirm that the estimation window can dramatically change abnormal returns due to shifting risk over time. Altogether, in line with some previous studies, these results suggest that firms experience negative CARs after SEOs and M&As. However, negative CARs are the result of short-run rather than long-run abnormal returns.

Repeating Tables B.2 and B.3 with random samples instead of matched samples as controls, the results are remarkably similar in Tables B.4 and B.5. Compared to earlier SEO results in Table B.2, the random control results in Table B.4 tend to exhibit somewhat higher t-statistics for significant events but the results are otherwise comparable. Likewise, the M&A results Tables B.3 and B.5 are virtually the same using matched versus random controls. Consistent with our discussion in the previous section, we infer that differencing abnormal returns zaps out missing factors (captured by Jensen's α) for the most part.

2.4.2 Risk Shifts

Our previous results in Tables B.2 and B.3 and Figures C.1 and C.2 suggest that risk is shifting around SEO and M&A event dates. To more formally test this conjecture, we investigate changes in market model betas before and after these corporate events. For this purpose, equation (2.6) is estimated using different pre- and post-event windows straddling the event day, including before and after periods of 15, 25, 42, 60, and 90 days (trading days). After estimating equation (2.6) for each individual stock, we test whether the dummy variable capturing a potential beta risk shift is significantly different from zero across all stocks.

The risk shift results for SEOs and M&As are shown in Table B.6. Due the possibility that confounding events may affect risk shifts of event stocks, we also test SEOs and M&As minus their matched control stocks. Average beta shifts captured by $\hat{\bar{\beta}}'$ in the last column suggest that risk significantly shifted in a number of the estimation windows. For SEOs in Panel A, significant positive beta shifts occur using 42, 60, and 90 days around event day T. Results for SEOs minus matched control in Panel B are consistent with using only SEOs. Additionally, market beta increases by about 10% for SEOs and as much as 30% for SEOs minus matched control stocks, which suggests that risk shifts are economically significant.

For M&As in Panel C of Table B.6, significant beta shifts occur in the 15 and 25 day event windows and are negative (rather than positive) in sign. However, beta shift results in Panel D for M&As minus matched control stocks are only marginally significant using the 15 day estimation window. The latter finding is consistent with the fact that M&As' abnormal returns disappear in a shorter post-event timeframe compared to SEOs, which implies lower power to detect risk shifts. On average, market beta decreases by approximately 5% to 10% after the event. This magnitude is smaller compared to SEOs but still economically significant. We infer from these results that major corporate events are associated with significant changes in market beta risk.[10]

[10]In unreported results, we fixed the before estimation window at 2 months and used different post-event windows

Given changing risk around corporate events, we estimate abnormal returns results using an estimation window that combines the 2 months before and 2 months after periods.[11] By using an estimation window that straddles the event day, abnormal returns are determined by their average levels around corporate events, as opposed by risk levels either before or after events. Tables B.7 and B.8 report the average abnormal return results for SEOs and M&As, respectively, for both the market model and the five-factor plus momentum model as well as findings for both matched and random controls. In Panel C of these tables, none of the t-statistics is significant with respect to average abnormal returns generated by the different models and return differences between event and control stocks. It is notable that the results are almost the same for the market model and five-factor plus momentum model. Hence, the market model is sufficient to adjust for risk in the estimation of long-run abnormal returns, as multifactors do not materially change the magnitudes of residual errors.

Figure C.3 illustrates time series of average daily betas for SEOs and M&As, in addition to share repurchases (SRs) used in forthcoming robustness checks,[12] during the five year post-event period. Panel A for SEOs shows that the average daily beta increases from around 0.98 to 1.10 for two months after events, decreases to around 0.90 after about one year, and becomes stable thereafter. Panel B for M&As reveals that beta risk levels are fairly stable after events but tend to increase gradually from about 0.85 to 0.90 in the fifth post-event year. Lastly, Panel C for SRs shows beta risk decreasing from about 0.73 to 0.67 within the first year and thereafter increasing to about 0.77 the end of the five-year, post-event period. These graphical results corroborate the results of our statistical tests that risk shifts occur after major corporate events.[13]

Concerning the post-event quarterly results in Panel D of Tables B.7 and B.8, none of the t-

to test risk shifts. Our findings are similar to Table B.6 and again show that risk continues to shift over time after corporate events. Also, we use the Fama and French five-factor model augmented with the momentum factor to test risk shifts. At least one factor loading significantly shifted in almost all tests.

[11] We also estimated abnormal returns using only the post-event estimation window. As before, no significant long-run abnormal returns are found. Moreover, short-run abnormal returns are positive which indicates risk shifting.

[12] To conserve space, similar SPLT results are available upon request.

[13] It is worth noting that, in our sampling procedures, we dropped small M&A deals. Also, share repurchases (SRs) occurred relatively infrequently among smaller firms compared to larger firms. Hence, compared to SEO firms, M&A and SR firms tend to relatively larger in our samples. These size differences help to explain the relatively higher beta risk of SEO firms compated to M&A and SR firms in Figure C.3.

statistics passes the 5 percent level of significance. However, in post-event quarter 1, we should mention that abnormal returns for SEOs in Panel D of Table B.7 are marginally significant at the 10 percent level (i.e., $t = 1.78$ and 1.69 using matched controls and random controls, respectively). Referring to previous findings, in Panel D of Tables B.2 and B.4, the t-statistics for the 2 months after estimation window in quarter 1 are highly significant (i.e., $t = 3.12$ and $t = 3.58$, respectively). Given the fact that results are insignificant using 2 months before estimation, this evidence suggests that risk parameters change during the quarter after SEOs. For M&As the evidence is less clear in this respect. In Panel D of Table B.8 for the 2 months after estimation window, average abnormal returns are negative and insignificant. Contrary to this finding, positive abnormal returns for M&As previously documented in Panel D of Tables B.3 and B.5 are not significant.

It is interesting that the event stocks' results in Panel A of Tables B.7 and B.8 are almost the same as those in Panel C for the event stocks minus control stocks. None of the t-statistics is significant for event stocks. Overall, compared to results using estimation windows before the event day, short-run abnormal returns disappear upon using a straddle estimation window. Since using the straddle estimation window is not a strategy that can be used by an investor in real time, we cannot conclude that short-run abnormal returns do not exist. However, the results in Tables B.7 and B.8 suggest that all abnormal return are explained after adjusting for more complete post-event market information. In this regard, it appears that the market needs some time to fully digest all information. Therefore, we infer that abnormal returns exist in the short term but not long term.

Figures C.4 and C.5 graphically display daily CARs for SEOs and M&As, respectively. Results are broken down for event stocks (Panel A), event stocks minus matched controls (Panel B), and event stocks minus random controls (Panel C). For SEOs in Figure C.4, the CAR pattern for event stocks is very similar to those for event stocks minus random control stocks – that is, initially positive CARs reverse toward zero and thereafter gradually trend downward. M&A event stocks in Figure C.5 again exhibit an initial positive CAR response that more sharply reverses to zero over approximately one month and then stabilizes around a zero abnormal return over the remainder of the five-year post event period. Like the SEO results, CARs in Panel B for event minus matched control stocks tend to be relatively flat over time around zero, whereas CARs in Panel C for event minus random control stocks trend downward and become gradually more negative over time. However, the lack of significance of abnormal returns in Tables B.7 and B.8 suggest that these trends are not significantly different. We infer that initial positive CARs for SEOs and M&As reverse within a short time span of a month or two and thereafter become insignificantly different from zero. In general, no long-run abnormal returns are evident for these major corporate events.

2.4.3 Comparative Analyses

Lastly, we comparatively examine SEO and M&A results using traditional BHAR and CTAR tests. In Table B.9 we see that, using both matched and random controls, these traditional methods typically find significant long-term abnormal return for SEOs and M&As. Comparing these methods, the BHAR method generates higher abnormal returns than the CTAR method, which better controls for risk in a market efficiency sense.[14] These long-run results are similar to those of other authors cited in the introduction.

2.4.4 Robustness Checks

We perform a number of robustness checks. First, tests of abnormal returns for stock repurchases (SRs) are run. We repeat the analyses in Tables B.7 and B.8 with an estimation window that straddles event days 2 months before and after event announcements. Again, as shown in Table B.10, none of the t-statistics is significant in Panels C; however, similar to SEOs, quarter 1 average abnormal returns are positive and significant. As before, the results for SR stocks in Panel A are similar to those for event minus control stocks in Panel C, and results for the market model and five-factor plus momentum model are very close to one another. Casual inspection of Figure C.6 again suggests an initial, short-run positive CAR after SR announcements as in the cases of SEOs and M&As but (rather than reversing those gains) CARs thereafter level off over the 5-year post-event period. Despite the lack of short-run reversal, SR results confirm our earlier inference of no

[14]To conserve space, similar SR and SPLT results are available upon request.

long-run abnormal returns.[15] Besides, Table B.16 reports similar results for stock splits (SPLTs). No significant abnormal returns are found except for the first quarter. The SPLT group yields similar results as the event minus control group does. Different control groups and asset pricing models do not affect the results. SPLTs results are consistent with our conclusion of no long-run abnormal returns as well.

Second, our sample period is divided into sub-periods 1980-1997 and 1998-2015 and earlier results in Tables B.7 and B.8 are repeated for SEOs, M&As, SRs, and SPLTs. Tables B.17 to B.24 report the results. In general, none of sub-period results detect any significant abnormal returns across these different event firms, which corroborates our main findings. Abnormal returns occur in sub-period 1980-1997 for SEOs and SPLTs in post-event quarter 1, but they are insignificant in sub-period 1998-2015. For SRs, abnormal returns occur in quarter 1 in both 1980-1997 and 1998-2015 sub-periods. Overall, sub-period analyses do not change our RPE results for the most part.

2.4.5 Simulation Analyses

Here we conduct simulation analyses to better understand the effects of risk shifts on our RPE abnormal return results relative to those of traditional methods. More specifically, based on SEO return data, we investigate Type I and II errors by hypothetically introducing risk shifts via simulation methods. Focusing on the RPE and CTAR methods and the CAPM market model, we implement the following simulation steps:

Step 1: A three year period is assumed. The first year is prior to SEO events. The SEO event occurs on the first day of the second year. Beta risk is allowed to shift in this second year. In the third year, the beta risk does not change. Each year contains 250 days.

Step 2: We create stock return series using actual SEO data. A total of 500 stocks are used in simulations. We randomly draw a market beta for each stock from the total SEO sample, which was estimated using one year of returns prior to the SEO event day. Each stock is

[15] In unreported results, while we did not generally find significant beta shifts for different estimation windows, at least one factor loading in the Fama and French five-factor model normally exhibited a significant shift.

randomly assigned with an event day within the range of our sample period. Daily returns for the CRSP market factor from French's website are downloaded in the three-year period. Residual terms for each stock are randomly drawn from a pool of real residuals based on the event year. For example, the residual terms for a stock for the first year after events are drawn from real residuals for a stock for the first year after event days.

Step 3: For the first year after event days, each beta is assumed to grow by 0.08%, 0.04%, or 0.02% each day and then stay constant thereafter in the third year. These three risk change scenarios correspond to approximately 20%, 10%, and 5% annual beta growth, respectively.[16] Different abnormal return scenarios are assumed at 1%, 0.5%, or 0.1% of total daily actual returns in the six-months after events and zero for all other times. We use these abnormal returns, betas, market factors, and residual terms to generate simulated returns using the CAPM market model.

Step 4: A six-month estimation window is used for the market model. We report the percentage of significant abnormal returns for both RPE and CTAR methods. We expect that the abnormal returns results will be affected by beta risk growth; as such, abnormal returns results are provided for each beta growth scenario.

Step 5: A total of 2000 simulations are run for each set of results.

According to our simulation design, simulated abnormal returns and risk shifting occur in the 6 months after an SEO event. From 6 to 18 months after an event, risk shifting continues to occur but with zero simulated abnormal returns. The last 6 months have no risk shifting and zero simulated abnormal returns. Table B.11 reports the percentage times out of 2000 simulations that a zero abnormal return is rejected at the 5% level for RPE and CTAR methods. Panel A reports results for 6 months after events. For all different alpha and beta levels, our RPE method rejects zero abnormal returns all the time, whereas CTAR rejects 82% to 84% of the time. Hence, our RPE method has the ability to capture simulated abnormal returns. In Panel B for 6 to 18 months with

[16] Beta changed more than 10% in our empirical tests reported above.

risk shifting but zero abnormal returns, our RPE method rejects zero abnormal returns 1% of the time, whereas CTAR rejects up to 89% of the time. In Panel C for the last 6 months, our RPE has a rejection rate of 1 to 2%, whereas CTAR rejects up to 34%. Overall, we infer from the simulation results in table B.11 that the RPE method controls Type I and II errors within a reasonable range. Risk shifting tends to induce the CTAR method to falsely reject zero abnormal returns.

2.5 Conclusions

A long-standing controversy exists on the existence of long-run abnormal returns after major corporate actions. This paper re-examined long-run abnormal returns by implementing a rolling prediction error (RPE) approach that adapts standard short-event study methods to a long-run perspective. Prediction errors are computed for each event day over a five-year, post-event period and subtracted from realized returns to estimate abnormal returns. Samples of seasoned equity offerings (SEOs) and mergers and acquisitions (M&As) over the period 1980 to 2015 are gathered. RPE tests take into account matched and random controls as well as different asset pricing models, including the market model, Fama and French (2015) five-factor model, and a five-factor plus momentum model. Comparative analyses are provided based on traditional BHAR and CTAR approaches. Robustness checks were conducted for share repurchases (SRs), stock splits (SPLTs) as well as different subperiods. Also, simulation tests are done to test the robustness of the RPE method to potential risk shifts.

Tests using different estimation windows for models suggested that risk shifts occur around SEO and M&A announcement dates. Symptomatic of shifting risk, abnormal returns become noticeably smaller as the estimation window is shortened prior to events. Using a post-event estimation window, abnormal returns tend to increase markedly, which further supports the possibility of risk shifts. Formal tests of the market model with dummy variables found that market beta significantly increased after SEOs and decreased after M&As. To better take into account risk shifts, we employed an estimation window that straddles the event day (viz., combining two months before and after events). These tests detected abnormal returns in the first few post-event months but not thereafter over a five-year, post-event period. Thus, initial short-run abnormal returns occur but not long-run abnormal returns. By contrast, traditional BHAR and CTAR methods generate significant long-run abnormal returns. These findings are confirmed: (1) with or without matched and random control samples, (2) for different asset pricing models including the CAPM market model, and (3) in robustness tests of share repurchases (SRs), stock splits (SPLTs) and different subperiod analyses. Simulation analyses with SEO data and the market model showed that the RPE method controls both Type I and II errors in a reasonable range for plausible shifts in beta risk. However, we found that the CTAR method falsely rejected zero abnormal returns due to risk shifting.

We conclude that, after dynamic risk adjustment, anomalous long-run abnormal returns are not evident after major corporate events. An important implication of our findings is that investors efficiently gauge risk and return of stocks in response to corporate actions. The market efficiency hypothesis is supported to the extent that post-event continuation of abnormal returns is not observed. Consistent with this hypothesis, Fama (1998, p. 304) has commented that long-run abnormal returns are fragile and tend to vanish after appropriate changes in empirical methodology, particularly adjustments for risk. Our new RPE method robustifies long-run event tests with respect to risk shifts associated with unexpected corporate events. Further research is recommended using the RPE method to investigate other anomalous stock return behaviors after corporate actions.

3. AN ASSET PRICING APPROACH TO ESTIMATING THE GLOBAL MINIMUM VARIANCE PORTFOLIO

3.1 Introduction

Seminal work by Nobel Laureate Harry Markowitz (1952, 1959) on the mean-variance investment parabola is famous for the concept of diversification and formation of efficient portfolios. Based on optimal weights of assets, efficient portfolios (hereafter denoted E) can be constructed with the highest Sharpe ratio for any given expected return or total risk level. To estimate optimal weights, it is necessary to compute expected excess returns as well as their associated variance-covariance matrix. These requirements have led to disappointing empirical results. One problem is that expected returns must be estimated over a long period (Merton (1980)). The second problem is that, as widely documented by many researchers (e.g., Jobson and Korkie (1980), Green and Hollifield (1992), Jagannathan and Ma (2003), and DeMiguel, Garlappi, and Uppal (2009b)), the variance-covariance matrix is difficult to reliably estimate.

Concerning the variance-covariance matrix problem, a vast literature has emerged in an attempt to overcome estimation errors. [1] In general, these studies fall into three branches. The first branch seeks to reduce matrix errors by means of shrinkage estimators or other non-Bayesian methods.[2] The second branch utilizes asset pricing models to set a priori matrix constraints.[3] The third, and last, branch employs portfolio rules such as short selling constraints.[4] Despite these diverse approaches and extensive efforts, DeMiguel, Garlappi, and Uppal (2009b) have found that the E portfolio does not outperform a naive $1/N$ strategy.

Closely-related literature focuses on the global minimum variance portfolio G that lies at the

[1] A full introduction of portfolio choice problem could be found in Brandt (2010), Ferson (2019).

[2] See studies by Jobson and Korkie (1980), Jobson and Korkie (1981b), Jorion (1985), Jorion (1986), Jorion (1991), Frost and Savarino (1986), Haugen and Baker (1991), Best and Grauer (1992), Chan, Karceski, and Lakonishok (1999), Ledoit and Wolf (2004), Ledoit and Wolf (2020), Clarke, de Silva, and Thorley (2006), Clarke, de Silva, and Thorley (2011), Maillet, Tokpavi, and Vaucher (2015), and others.

[3] See studies by Black and Litterman (1992), Clarke, de Silva, and Thorley (2006), Michaud (1989), Pástor (2000), Pástor and Stambaugh (2000), and others.

[4] See studies by Frost and Savarino (1988), Jagannathan and Ma (2003), Garlappi, Uppal, and Wang (2007), Kan and Zhou (2007), DeMiguel, Garlappi, Nogales, and Uppal (2009a), and others.

vertex of the symmetry axis and divides the mean-variance parabola into two symmetric halves. Similar to portfolio E, existing methods for estimating G require the estimation of the variance-covariance matrix. Encouraging results in previous studies have shown that low variance diversified portfolios outperform other diversified portfolios.[5] This phenomenon is known as the low volatility anomaly (Baker, Bradley, and Wurgler (2011), Ang, Hodrick, Xing, and Zhang (2006), and others).

We hypothesize that the low volatility anomaly arises from the fact that low variance portfolio G is not affected as much by estimation errors as portfolio E with higher variance. With the same estimation errors, the effects are naturally larger in portfolio E than G due to its higher relative standard deviation of returns and, therefore, different locations within the mean-variance parabola. More specifically, we argue that the width of the parabola contributes to estimation errors possible in constructing an efficient portfolio at a given risk level. Since the true portfolio G always has zero cross-sectional return dispersion, which is less than all E portfolios, mistakes possible when estimating portfolio G will be reduced. Given the horizontal axis of symmetry at the true G portfolio's expected return, the minimum variance frontier is symmetric around this axis. Any well-diversified portfolio will move toward the minimum variance boundary of the parabola. In this regard, the portfolio could move either to the upper-left or lower-left depending on whether more weights are given to assets with expected returns higher or lower than the axis of symmetry.

Using this simple logic, large assets with on average lower expected returns but higher weights than other assets could have adverse effects on building an efficient portfolio. No matter what methods are used to reduce estimation errors, it is important to reduce the number of parameters to estimate. As such, it is common to use some predetermined portfolios to start the optimization process. When predetermined portfolios are value-weighted, the adverse effects from large assets are magnified. To estimate a more efficient portfolio E, we want to eliminate assets whose expected returns are below the G portfolio. Despite performing well, the construction of portfolio G using

[5] See Chan, Karceski, and Lakonishok (1999), Clarke, de Silva, and Thorley (2006), Clarke, de Silva, and Thorley (2011), Haugen and Baker (1991), Haugen and Baker (2012), Jagannathan and Ma (2003), Jorion (1985), Jorion (1986), and others.

existing methods may underestimate the expected return due to estimation errors.

In this paper, we propose an alternative empirical method to estimate portfolio G without the variance-covariance matrix. The intuition is straightforward. We weight assets with less exposure to idiosyncratic risk (close to the efficient frontier) more heavily, ensure a large number of assets for diversification purposes, and pick those assets with the lowest systematic risk. Based on a valid asset pricing model, we first form portfolios with different risk levels and weight individual assets by the inverse of residual variance from a time-series regression estimation of the model. We use residual variance to assign higher weights to individual assets that are closer to the minimum-variance efficiency. Supporting this approach, as argued by Chan, Karceski, and Lakonishok (1999), the full variance-covariance matrix could be affected by firm-specific events that contribute to instability. To mitigate these effects, they suggest using information from idiosyncratic components. After selecting close-to-efficient portfolios at different risk levels, we pick those with the lowest risk level and weight them by the inverse of variance to get portfolio G. This process is rolled forward one month each time, accounting for varying discount rate as discussed in Cochrane (2011). All portfolio G returns are computed using out-of-sample (one-month-ahead) returns.

Our new approach to estimating portfolio G has several advantages. First and foremost, by excluding estimates of the variance-covariance matrix, we avoid estimation errors documented in earlier literature. Second, our method utilizes the universe of available assets. It is not necessary to filter data via initial portfolios as long as data is not missing. With no need to reduce the number of pairwise covariances to be estimated, our method does not need to use any predetermined portfolios that are value- or equal-weighted. Third, and last, our method is easy to implement. Anyone with the ability to sort and run OLS regressions can readily implement our methods.

We test and compare the variances, expected returns, and Sharpe ratios of our portfolio G and the market portfolio as proxied by the CRSP index. For the full sample period, portfolio G has less than 50% of the market portfolio variance. Additionally, our portfolio G achieves a more than 100% increase in the Sharpe ratio relative to the market portfolio. Graphical analyses demonstrate that the time-series trend in portfolio G returns is very similar to the market portfolio but with less extreme values. These empirical results support our research hypothesis that estimation errors mainly affect the expected returns of portfolio G. Our results are consistent using several different asset pricing models and subperiods. Importantly, portfolio G is not dominated by individual assets or vulnerable to extreme weights. As an actively-managed portfolio, portfolio G has a turnover ratio approximately five times larger than the index. However, after considering real transaction costs, the Sharpe ratio outperformance is not affected. Further analyses repeat our G formation process using only large-capitalization stocks. As expected, without significantly increasing the variance, portfolio G containing only large assets has substantially lower expected returns than otherwise. These results confirm that large assets with higher value weights can adversely affect portfolio G.

The rest of the paper is organized as follows. Section 3.2 discusses the estimation error differences between portfolios G and E as well as the adverse effects of large assets on their estimation. Section 3.3 describes our dataset and proposed method for building portfolio G. Section 3.4 contains the empirical results, including robustness checks. Section 3.5 concludes.

3.2 Expected Returns

3.2.1 Portfolios G and E

In extensive empirical tests of equity datasets as well as simulated data, DeMiguel, Garlappi, and Uppal (2009b) reported evidence that portfolio E could not beat a $1/N$ portfolio due to estimation errors more than offsetting optimal diversification gains. By contrast, as mentioned earlier, consistent with the low volatility anomaly, researchers have documented that portfolio G outperforms the market portfolio. Haugen and Baker (2012) attributed this anomaly to investors chasing high returns in the equity market. These stocks have higher risks than other stocks and tend to attract media coverage. As the demand for these stocks rises, their risk premium decreases. They inferred that estimation errors offset gains from optimal diversification. However, according to Merton (1980), Green and Hollifield (1992), and Jagannathan and Ma (2003), estimation errors in expected returns and the variance-covariance matrix should be the same for both G and E portfolios. If these errors are large enough that a naive 1/N strategy performs the same or better than portfolio E, what mitigates similar errors in portfolio G?

Figure E.1 illustrates our explanation for the differential performance of portfolios G and E. As proposed by Markowitz (1952) (also see Merton (1972)), a hypothetical minimum-variance boundary is shown, where the X-axis is time-series standard deviation of returns, and the Y-axis is expected returns. Numbers 1 to 4 represent four different well-diversified groups of assets. $S1$ and $S2$ denote one and two standard deviations, respectively. Letters A, B, A', and B' denote four different expected returns with relations $A' < B' < B < A$. We further assume that: $S2$ and A are the true standard deviation and true expected return for portfolio E, respectively; $S1$ is the true standard deviation for portfolio G; and all portfolios are long with no short positions.

To construct portfolio E, assets in group 1 offer relatively higher expected returns commensurate with those of portfolio E. Consequently, group 1 assets *optimally* are more likely to be more heavily weighted than other assets in portfolio E. Due to variance reduction through diversification, the portfolio's standard deviation decreases to $S2$. The expected return will be A, which is some average of returns of assets in group 1. Given the existence of estimation errors, the *worst* case in attempting to find portfolio E is mistakenly using assets in group 2. Given sufficient diversification, the portfolio's standard deviation will decrease to approximately $S2$ with an expected return equal to A'. The maximum mistake in terms of expected return one can make in estimating portfolio E with standard deviation $S2$ will be $A - A'$. Without loss of generality, for portfolio G, the *optimal* case uses assets in group 3, while the *worst* case contains assets in group 4. The maximum mistake in estimating the expected return of portfolio G with a standard deviation of $S1$ will be $B - B'$. Since $A' < B' < B < A$, we know that $(A - A')$ is larger than $(B - B')$. Therefore, even if the same estimation errors exist in both G and E portfolios, their effects on the final portfolio will be larger in E than G.

Figure E.1 suggests that, as the width of the parabola widens with increased risk as measured by the standard deviation of returns, potential errors in estimating expected returns are invariably larger for portfolio E than portfolio G. In other words, the larger the true standard deviation of portfolio E, the greater the propensity for estimation errors. Also, although the overall performance of portfolio G is good, its expected return could be underestimated due to estimation errors.

3.2.2 Large Assets

Figure E.1 enables insights into the potential effects of large assets on portfolios G and E. It is well known (e.g., Fama and French (1992)) that small stocks on average have higher expected returns than large stocks. Therefore, small (large) stocks are more likely to have higher (lower) expected returns than the true portfolio B. As illustrated, small assets are more likely to be in groups 1 and 3, whereas large assets are more likely to be in groups 2 and 4. If weighted more heavily, large assets will potentially drive down the expected returns of portfolios G and E. In forthcoming Section 3.4.4, we empirically show that, based on the largest 1,000 stocks, expected returns of portfolio G are reduced without changing its volatility.

Previous studies have utilized shrinkage methods, factor models, and portfolio constraints in efforts to reduce the number of pairwise covariance estimates for constructing portfolio G. They either choose portfolios that have already been built (such as industry portfolios, Fama and French portfolios, etc.[6]) or pick a small number of (large) individual assets[7] to start the optimizing process. Most portfolios are value-weighted portfolios, which means that, no matter how weights change for each portfolio, the final portfolio's expected return tilts toward large assets. This weighting approach will lower the expected returns of portfolios G and E. In this paper, because it is not necessary to estimate the variance-covariance matrix, we are able to employ the entire universe of stocks and mitigate size effects.

3.3 Data,Methodology and Performance Evaluation

3.3.1 Data

We downloaded common stock returns from the Center for Research in Security Prices (CRSP) database. Since portfolio G spans the whole market, we use all firms incorporated in the U.S. with

[6]For example, see Jagannathan and Ma (2003) and DeMiguel, Garlappi, Nogales, and Uppal (2009a).
[7]For example, see Haugen and Baker (1991) and Clarke, de Silva, and Thorley (2006).

CRSP share codes 10 or 11. The sample period is from January 1968 to December 2019. The year 1968 was selected to reduce problems with missing daily return data and be consistent with previous studies for comparison purposes (e.g., Clarke, de Silva, and Thorley (2006)). Stocks are required to have at least 245 days of non-missing return data during a one-year estimation window. The only exception to this filter is during the paper crisis from August 1968 to November 1969, in which 220 days of non-missing return data are required.

Return series for both value- and equal-weighted CRSP market indexes are downloaded. Since we construct portfolio G using a subset of common stocks in the CRSP index with share codes 10 and 11, we also utilize the corresponding value-weighted market index from French's website[8] and compute its companion equal-weighted market index. Lastly, daily return size and value factors for the Fama and French (1992) and Fama and French (1993) three-factor model as well as momentum factor are also downloaded from French's website.

3.3.2 Methodology

Here we propose a new method for building portfolio G. We allow only long positions in stocks for three reasons. First, short sales may not be possible in actual practice. Second, a short sale constraint is commonly used in previous studies of portfolio G (e.g., Frost and Savarino (1988) and Jagannathan and Ma (2003)). Third, and last, we posit that portfolio G must be a long-only portfolio. As proof, assume that the minimum variance portfolio is not pure long but instead contains some short positions. This portfolio can be decomposed as follows:

$$P_{MV} = P_L + P_{LS}, \tag{3.1}$$

where P_L is a pure long portfolio, and P_{LS} is a zero-investment portfolio. The number of assets is sufficiently large to allow many different decompositions of P_{MV}. It is reasonable to believe that there exists with almost certainty at least one unique pair of portfolios P_L and P_{LS} with non-negative covariance. In this case we can define $Var(P_{MV}) = Var(P_L + P_{LS}) = Var(P_L) +$

[8] See https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.

$Var(P_{LS}) + 2Cov(P_L, P_{LS}) \geq Var(P_L) + Var(P_{LS})$. Pure long portfolio P_L has a smaller variance than minimum portfolio P_{MV}, which implies that the minimum variance portfolio must be pure long, or $Var(P_{MV}) = Var(P_{LMV})$, where P_{LMV} is the long minimum variance portfolio. Because there is only one minimum variance portfolio, this result must hold even if P_L and P_{LS} have negative covariance.

Market risk is multidimensional – that is, each component of market risk contributes to its volatility in an asset's observed time-series performance of returns. It is natural to weight each asset by the inverse of its measured variance. Under the ideal case in which the covariance matrix of all assets is diagonal, the formed portfolio is exactly the true minimum variance portfolio. However, for a strongly correlated market, the formed portfolio may not be a good proxy for the minimum variance portfolio.

Intuitively, building portfolio G is a process of comparison between individual assets. Some assets get a higher weight compared to others. Portfolio G has three basic qualities: (1) it is well diversified, (2) it is relatively efficient (i.e., close to the minimum-variance frontier with low exposure to idiosyncratic risk), and (3) it has the lowest variance of portfolio returns. In view of these criteria, we propose the following model dependent method:

Step 1: Assume that the valid asset pricing model is:

$$R_i(t) = \alpha + \sum_{k=1}^{K} \beta_k f_k(t) + \varepsilon_i(t),\ i = 1, \cdots, N, \tag{3.2}$$

where $R_i(t)$ is the return on the ith stock on day t in the estimation period comprised of N days, $f_k(t)$ is the kth factor return ($k = 1, ..., K$), and $\varepsilon_i(t) \sim$ iid N(0,σ_i^2). For each calendar month T in the total sample period, we choose the year before T as the estimation period. Using daily data, we run regression equation (3.2) to obtain K betas for each asset.[9] The

[9] As mentioned by Scholes and Williams (1977) and Dimson (1979), nonsynchronous trading could be an issue using daily data. For this reason, we repeated all of our tests using the Dimson (1979) aggregate beta method. Not surprisingly, our results are unchanged for the most part. As recognized by some event study researchers (e.g., Brown and Warner (1985) and Section 2), the main effects of nonsynchronous trading are absorbed by α, and thus residual terms are not materially affected.

variance of residuals for each asset is calculated and stored as $Var(\varepsilon_i)$.

Step 2: For each estimation window, stocks are sorted by beta within each of L groups, thereby forming L^K portfolios. For example, if we have $K = 2$ factors and each factor is sorted into $L = 10$ groups, we form $10^2 = 100$ portfolios. Here we keep only M portfolios with the lowest betas (to be discussed shortly). For each portfolio, we weight each asset by the inverse of the variance of error term $Var(\varepsilon_i)$ from step 1. This ratio is recorded as weight 1 (w_1).

Step 3: Using weight 1 as the initial weight for each asset, we let each asset grow naturally by its returns during the one-year estimation window. At the end of the year, we record the value of each asset as weight 2 (w_2). Also, we calculate the variance of the L^K portfolios during the one year as $Var(P)$. We then record the inverse of each portfolio's variance $Var(P)$ as weight 3 (w_3) for each portfolio.

Step 4: We now have a within portfolio weight for each asset and portfolio weight for each portfolio. For each calendar month T, we use $w_2 x w_3$ as the initial weight for each asset to form a portfolio. This portfolio G is held for one month and its return is recorded. Finally, portfolio G is rebalanced every month until the end of the sample period.

Following the steps above to form portfolio G, we employ three alternative asset pricing models: (1) CAPM market model of Sharpe (1963), Sharpe (1964), and Fama (1968) based on the market factor, (2) Fama and French (1992) and Fama and French (1993) three-factor model based on the market factor plus size and value factors, and (3) Carhart (1997) four-factor model based on these three factors plus momentum factor. Given that estimation errors have diminished effects on portfolio G and these time-series regression models have similar residual error variances, we anticipate that portfolio G will be similar across these models. Intuitively, a model with a better fit to the data may improve portfolio G. Consequently, in our empirical tests, we include a recently proposed ZCAPM asset pricing model by Liu, Kolari, and Huang (2019) based on the market factor and a cross-sectional return dispersion factor.

Ideally, we want to sort stocks into as many portfolios as possible in terms of L groups. Our goal here is to sort stocks into different risk groups. Stocks in the same group are viewed to have similar risks. Among stocks in each group, we place more weight on those closer to the frontier with lower residual variance. However, if too many groups are formed, we will have less well-diversified portfolios with lower numbers of stocks, which will tend to increase their variance. Therefore, we need to balance L to ensure diversification within each portfolio yet build as many portfolios as possible. For the CAPM market model, ZCAPM, and Fama-French three-factor model, we set L to 64, 8, and 4, respectively, such that each model yields 64 portfolios in total. Given our sample period, each portfolio has, on average, around 40 to 50 individual assets. For the Carhart four-factor model, we set L equal to 3 to yield 81 portfolios.[10]

In step 2 above, the intuition behind the choice of M low beta portfolios is straightforward. Because portfolios formed in Step 2 are close to the minimum-variance frontier, little additional diversification is possible. To get the lowest variance portfolio G, we need portfolios with the lowest variance (lowest risk level). For the CAPM market model, ZCAPM model, and Fama-French three-factor model, we chose to select 8-out-of-64 portfolios from Step 2 with the lowest risk levels. For the Carhart model, we select the lowest 9-out-of-81 risk portfolios from Step 2. These selections guarantee that at least around 100 individual assets will be included in the final portfolio G in the sample period. This number coincides with the lowest number of assets used to build the G portfolio in previous studies (e.g., Clarke, de Silva, and Thorley (2006)).[11]

A major issue in our analyses is liquidity. Suppose an illiquid stock has all zero daily returns during a full year, which implies zero residual variance and zero return variance. If included in our G portfolio, such a stock would get an extremely high weight in G, and the G portfolio's low variance would be distorted. The simplest way to mitigate this potential problem is to restrict

[10]In unreported results, we experimented with lower and higher numbers of portfolios (e.g., 20 or 100 portfolios). However, we found that results are improved by using 64 portfolios. It is likely that, if the number of assets were very large, 100 portfolios would have improved performance. Given that our analyses span a long sample period when the number of stocks ranges from around 1,000 to 7,000, the use of 64 portfolios appears to be a suitable choice.

[11]In unreported results, we repeated the analyses by incrementally changing the number of portfolios from only 4 to all portfolios. The performance of G significantly worsens only after more than half of portfolios are utilized. We infer that G's performance is not highly sensitive to the choice of M.

the analyses to some proportion of the largest stocks. However, as argued in Section 3.2 and documented in forthcoming Section 3.4.4, using only the largest stocks can bias portfolio G.

To deal with the liquidity issue, we first drop the 10% smallest stocks by market capitalization. Next, we experimented with applying the Amihud (2002) illiquidity measure, a ratio of absolute daily return to trading volume. The higher the ratio, the more illiquid an asset, which should be dropped. However, our one-year estimation window is a limiting factor. Suppose that a stock has mostly zero daily returns during the year with positive trading volume.[12] This stock will have a minimal illiquidity ratio but would not help to resolve our liquidity problem. Moreover, according to Chen, Eaton, and Paye (2018), most liquidity measures embed market volatility by construction. To avoid confounding these two characteristics, Lesmond, Ogden, and Trzcinka (1999) proposed counting the number of days with zero return to measure illiquidity. Consistent with this approach, we drop stocks with more than 50% zero return days during the one-year estimation window. A 50% cutoff was chosen to be slightly higher than the lowest maximum proportion of zero return days among different deciles of firms (see Table 1 in Lesmond, Ogden, and Trzcinka (1999)).

In addition to the filters described above, we drop assets whose volatility is less than 20% of the CRSP index during the same period. Some stocks that experience corporate events tend to have a stable price for a period of time. This 20% filter drops these stocks. Excluding the omission of the 10% smallest stocks, all other filters drop less than 5% of stocks in total (i.e., the size filter mitigates most of the liquidity issue). Similar to previous studies, our final filter to avoid an extreme weight on one asset in step 2 is to set the maximum weight at 15% for any individual asset in a portfolio. Further details of these filters are provided in forthcoming Section 3.4.3.

3.3.3 Performance Evaluation

To evaluate the performance of G portfolios, the following procedure is used: (1) estimate weights for each stock during an in-sample estimation window, (2) compute one-month-ahead

[12] Based on our data, it is quite common for a stock to have this profile, which appears to be attributable to different data recording methods by NYSE, AMEX, and Nasdaq. For example, price data is recorded as of 4 pm by Nasdaq. However, the daily trading volume includes after-hours trading. Trade details for exchanges can be found in the CRSP database variable descriptions.

(out-of-sample) returns for portfolio G, and (3) roll forward one at a time to construct a time-series of out-of-sample monthly G returns. For comparative purposes, this *rolling-sample* process is repeated for each asset pricing model to obtain time-series of monthly G returns.

Because G represents the global minimum variance portfolio, the variance of returns is a focal variable. While this variance is simple to calculate, there can be complications in testing whether the variance of two G portfolios is significantly different from one another. As noted by Ledoit and Wolf (2011), the traditional F-test for variance is invalid due to correlated returns, large tail returns, and the nature of time series. They proposed a new test method based on a studentized time-series bootstrap confidence interval, with significance determined by whether the interval contains one. We implemented both traditional and new test methods in their paper. Programming codes for these tests are downloaded from Michael Wolf's website.

Next, we want to compare alternative G portfolios' return performance estimated from different asset pricing models. For model p, we calculate the average out-of-sample monthly excess returns as μ_p and standard deviation as σ_p. Subsequently, the Sharpe ratio can be computed as:

$$SR = \mu_p/\sigma_p. \tag{3.3}$$

Two methods are used to test whether the Sharpe ratio of any two strategies differs significantly from another. Following DeMiguel, Garlappi, and Uppal (2009b), we employ the approach suggested by Jobson and Korkie (1981a) and modified by Memmel (2003). We find that all forthcoming test results using this method are statistically significant at the 1% level. However, for the method to be valid, returns are unrealistically required to be independently and identically normally distributed. For this reason, we also report p-values computed as in Ledoit and Wolf (2008). Similar to the test proposed by Ledoit and Wolf (2011), this method builds a studentized bootstrap confidence interval but tests for significance when zero is not contained in the interval. Adopting their method, we calculate the p-value using a 5000 iterative bootstrap with block size 5. For details of this test procedure, including a short-cut method for calculating corresponding p-values, see Ledoit and Wolf (2008).

Another important issue in constructing portfolio G is rebalancing. Higher turnover and related higher transaction costs can cancel G's higher expected return compared to a general market index portfolio. Following DeMiguel, Garlappi, and Uppal (2009b), we calculate turnover as the average percentage of total assets traded at each rebalancing:

$$Turnover = 1/623 * \sum_{t=1}^{623} \sum_{n=1}^{N} (|w_{p,n,t+1} - w_{p,n,t^+}|), \tag{3.4}$$

where 623 is the total number of months for our sample period minus one, and portfolio weight $w_{p,n,t+1}$ corresponds to the nth stock using model p after rebalancing. The latter weight is used in the next month. The weight w_{p,n,t^+} coincides with the portfolio before rebalancing at the end of each month. We do not calculate the turnover for the first month, which equals 100% for any strategy. Individual stock n is a constituent of portfolio G, and N is the total number of stocks in G. As the number of tradeable assets in the market changes over time, N changes.

In addition to portfolio turnover, we report the expected excess return and Sharpe ratio net of transaction costs. Following DeMiguel, Garlappi, and Uppal (2009b), we set proportional transaction costs (c) to 50 basis points per transaction. The raw return net of transaction costs is defined as:

$$R_t^{net} = (1 - c * \sum_{n=1}^{N} (|w_{p,n,t+1} - w_{p,n,t^+}|)) * (1 + R_{p,t}) - 1, \tag{3.5}$$

where $R_{p,t}$ is the raw return using model p at time t, and other notation is as before. The Sharpe ratio net of transaction costs is calculated using equation (3.3), where μ_p is the mean of R_t^{net}.

3.4 Empirical Results

Here we report the performance of G portfolios estimated from different asset pricing models. We denote the results as follows: G-CAPM, G-FF3, G-C4, and G-ZCAPM, where CAPM is the market model, FF3 is the Fama and French three-factor model, C4 is the Carhart four-factor model, and ZCAPM is the Kolari, Liu, and Huang empirical ZCAPM. Relevant benchmarks are the equal- and value-weighted CRSP indexes denoted CRSP-EW and CRSP-VW, respectively. Because we use all U.S. firms with CRSP share codes 10 or 11, we also report the equal- and value-weighted market index portfolios denoted EW and VW, respectively. Expected excess returns and standard deviations of returns are calculated on an out-of-sample basis.

As discussed above, to lower the number of pairwise covariance estimates, previous studies reduce the number of tradable stocks in portfolio G. By contrast, our approach seeks to use as many stocks as possible. Due to substantial differences in constituent stocks, our G portfolios are not comparable to those based on previous methods. Consequently, we compare our G portfolios to market index portfolios, which are widely used in academic research and professional practice as benchmarks.

3.4.1 Variance

Table D.1 reports the out-of-sample monthly variance of each portfolio. Each row represents a different portfolio. The second column gives the raw variance. As anticipated, G portfolios built based on different asset pricing models exhibit almost identical variance. All four G portfolios have variances in the range of 9-10 basis points. These findings confirm that the construction of G portfolios is not model dependant. Additionally, the similarity of variance suggests that the G portfolio is not subject to minor estimation differences.

The variances of the CRSP index and market index portfolios are almost identical. The variance is 20 basis points for value-weighted portfolios and only slightly higher at 30 basis points for equal-weighted portfolios. Columns 3 and 4 in Table D.1 report the percentage change of the G portfolios' variances compared to those of the VW and EW portfolios. G portfolios have about 55% (72%) lower variance than value-weighted (equal-weighted) market portfolios. Using testing methods by Ledoit and Wolf (2011), these differences are statistically significant at the 1% or lower level with p-value = 0.000. In DeMiguel, Garlappi, Nogales, and Uppal (2009a), compared to market indexes, their G portfolios had about 22% to 67% lower variance. In Maillet, Tokpavi, and Vaucher (2015) this differential is about 54% to 69%, which is quite good. However, during their sample period, we show in forthcoming results that our G portfolios have 81% to 90% lower variance than market indexes. G portfolios in Clarke, de Silva, and Thorley (2006) achieved a

33% to 53% variance decrease. And, in Jagannathan and Ma (2003), the corresponding reduction is about 37% to 65%. In sum, similar to these studies, our G portfolios have lower variance compared to market indexes.

To illustrate G's reduction in variance relative to the market index, Figure E.2 plots a 60-month rolling variance of the G-FF3 and VW portfolios. For each month starting from January 1973 to the end of our sample period, we calculate the variance of excess returns during the previous 60 months for each portfolio and graphically plot them. The figure shows that the G portfolio has a lower variance than the VW portfolio for all five-year rolling periods. These results are consistent with findings in Clarke, de Silva, and Thorley (2006), who reduce variance via existing methods based on the variance-covariance matrix.

3.4.2 Return and Sharpe Ratio

As discussed in Section 3.2, due to estimation errors in the variance-covariance matrix, even though a low variance may be achieved, the expected return is likely to be underestimated. Table D.2 reports the expected excess returns and Sharpe ratio for each portfolio. Again, the CRSP index and market portfolios have similar expected returns and Sharpe ratios. For value- and equal-weighted portfolios, expected returns are around 0.52% and 0.65%, respectively, with similar Sharpe ratios in the range of 0.11 to 0.12.

Again, the results are similar across different G portfolios. G-CAPM and G-ZCAPM have the expected returns equal to 0.82%, G-FF3 earns 0.80%, and G-C4 earns 0.76% on average. Compared to the market index portfolios, even the lowest G portfolio has a 13% higher return than the highest market index portfolio. Comparing returns and variances, the G-portfolios have very high Sharpe ratios (i.e., G-CAPM, G-FF3, G-C4, and G-ZCAPM have Sharpe ratios equal to 0.273, 0.264, 0.245, and 0.266, respectively) relative to market portfolios (i.e., CRSP-VW, CRSP-EW, VW, and EW equal to 0.113, 0.120, 0.117, and 0.114, respectively.) The last two columns show the percentage change in Sharpe ratios compared to the VW and EW portfolios. Except for G-C4, G portfolios based on the other three models increase the Sharpe ratio relative to the market portfolio by about 125% to 140%. In all cases, the monthly Sharpe ratio is more than double that of the market portfolios. Testing the difference of Sharpe ratios using methods in DeMiguel, Garlappi, and Uppal (2009b) and Ledoit and Wolf (2008), both tests indicate large, significant differences at the 1% or lower level with p-value = 0.000.

G portfolios in DeMiguel, Garlappi, Nogales, and Uppal (2009a) have around 12% to 75% higher Sharpe ratio than market index portfolios. Comparable percentages in Maillet, Tokpavi, and Vaucher (2015) are from -2% to 36%, in Clarke, de Silva, and Thorley (2006) from 14% to 80%, and in Jagannathan and Ma (2003) from 30% to 56%. In sum, large increases in both expected returns and Sharpe ratios are achieved using our asset pricing model approach to constructing G portfolios. Also, the evidence supports our hypothesis that estimation errors have large effects on expected returns.

3.4.3 Extreme Weights, Portfolio Turnover, and Net Transaction Costs

Even though our G portfolios perform well in terms of both expected returns and variances, it is worthwhile to explore the effects of individual stock composition on G (e.g., Best and Grauer (1991)). One possible issue is the possibility that several individual stocks dominate the portfolio. Panel A of Table D.3 reports summary statistics for individual stock weights in G portfolios. All G portfolios based on different models have a consistent average individual weight of 0.23%, which is considerably higher than the average weight of only 0.02% for the VW portfolio. This difference is attributable to incorporating only stocks with the lowest risk profile in G portfolios. All portfolios in Table D.3 have the same 0.00% minimum and similar maximum weights around 11%.[13] The standard deviation of the G portfolio weights is higher than the VW portfolio but relatively low in general.

When building G portfolios, we follow previous literature (e.g., Haugen and Baker (1991), Jagannathan and Ma (2003)) by setting a maximum weight for individual stocks. In our portfolios, we allow a maximum 15% weight for each individual stock in the M portfolios in Step 2. This constraint affects the final weights, as reported in Table D.3. In unreported results, we varied this

[13] In unreported results, we find that over 624 sample months, only 40 months have a stock weight of more than 3%.

constraint from 5% to 50%. Results tend to worsen when the constraint is below 10%[14] but are similar when it is above 15%. These results confirm that several individual stocks do not dominate our G portfolio.

Figure E.3 plots the monthly returns of the G-FF3 and VW portfolios. By casual inspection, performance is not driven by extreme values in selected months. As anticipated, G-FF3 has a similar time-series trend that is highly correlated with the VW portfolio. Even so, G-FF3 has less extreme high and low returns than VW. Hence, G-FF3 mimics overall market trends but is less volatile over time.

Another potential issue affecting portfolio G, particularly for practitioners, is portfolio turnover and related transaction costs. Panel B in Table D.3 reports turnover for each portfolio calculated using equation (3.4). As a passively-managed portfolio, VW has the lowest monthly turnover of 7.5%. Among our G portfolios, G-CAPM has the lowest turnover of 31.86%. G-FF3 and G-ZCAPM have turnover rates of 38.74% and 40.96%, respectively. G-C4 has a surprisingly high turnover rate of 64.59%, to be discussed shortly. On average, our G portfolios have turnovers about five times higher than that of VW. Compared to previous studies, such as DeMiguel, Garlappi, and Uppal (2009b) and DeMiguel, Garlappi, Nogales, and Uppal (2009a), our turnover results are within the range of their G portfolios.

To further investigate turnover rate, Panel C in Table D.3 provides expected returns and Sharpe ratios using the net excess return after transaction costs estimated using equation (3.5). With the exception of G-C4, G portfolios have net excess returns higher than 0.60% compared to the VW portfolio at 0.49%. Without sacrificing variance, G-CAPM, G-FF3, and G-ZCAPM still have Sharpe ratios approximately two times larger than VW.

We should note that G-C4 underperforms relative to the other G portfolios. As discussed earlier, G-C4 has a relatively high variance and low expected return. These attributes are due to a number of factors. When we sort individual assets into portfolios based on their betas, we need to control the number M of portfolios to ensure diversification. As the number of factors increases for the

[14] A lower maximum value reduces weights for many stocks that deserve a high weight and increases the weights of other stocks that deserve a lower weight, which diminishes G portfolio performance.

asset pricing model, the number of groups we can sort for each factor decreases. In the case of G-C4, for each beta, assets are sorted into only two groups. This sorting causes some individual stocks to jump in and out with more frequency than the other G portfolios. Given that betas have estimation errors, the sorting process does not help eliminate some stocks with high-risk profiles. In unreported results, we randomly selected two-out-of-the-four factors as sorting factors. Using the G-C4 model to estimate betas but sorting stocks based on only two factors, we find that G-C4 now performs similar to other models. These results confirm that dimunition in portfolio G performance is attributable to the number of factors in a model that affects our sorting process.

Overall, our G-portfolios are not materially influenced by any individual stocks or extreme values. These portfolios mimic market time-series trends but are relatively less volatile than general market portfolios. Also, although they demonstrate moderate portfolio turnover, their performance results are not affected by transaction costs.

3.4.4 Portfolio G with Only Large Stocks

As discussed earlier, large stocks play an important role in G portfolios constructed from existing methods. Here we rebuild our G portfolios using the largest 1,000 stocks by market capitalization from the CRSP database. Table D.4 reports the results. Compared to Table D.2, the variance of G portfolios using only large stock ranges from 0.0010 to 0.0011, which is similar to that of G portfolios using all stocks ranging from 0.0009 to 0.0010. Variance changes relative to VW now range from -50% to -44% and are statistically different from zero at a 1% or lower level with p-values = 0.000. Overall, the variance increases only slightly by using large stocks.

Unlike the variance, the expected monthly returns of G portfolios using only large stocks now ranges from 0.57% to 0.60%, a substantial decrease compared to results in Table D.2. Of course, this large decrease in returns reduces the Sharpe ratio. From the last column of Table D.4, we see that the Sharpe ratio of G portfolios is around 50% higher compared to VW. Recall that this relative value was more than 100% in Table D.2. Besides the changes in absolute value, the confidence levels of the Sharpe ratio differences decrease (i.e., the Sharpe ratio difference is only significant at a nominal 10% level for G-FF3 with p-value = 0.053). For G-CAPM, G-C4, and G-ZCAPM, these differences are now significant at the 5% level with p-values equal to 0.045, 0.029, and 0.033, respectively.

Overall, using large stocks in G portfolios slightly increases variance but substantially decreases expected returns and, in turn, Sharpe ratios. Referring back to Figure E.1, the G portfolio moves in a southeast direction inside the parabola. These results corroborate that estimation errors in the G portfolio primarily affect expected returns rather than variances.

3.4.5 Robustness Checks

As a robustness check, we divide our sample period into several subperiods. The results for VW, EW, and our G portfolios are shown in Table D.5. Subperiods are chosen from existing literature for comparative purposes. Panel A reports results from April 1968 to April 2005, which is the sample period in Clarke, de Silva, and Thorley (2006) and DeMiguel, Garlappi, Nogales, and Uppal (2009a). Panel B covers April 1973 to April 1997, which was used by Chan, Karceski, and Lakonishok (1999). And, Panel C focuses on January 2000 to December 2013 in line with the sample period in Maillet, Tokpavi, and Vaucher (2015).

In general, results in different subperiods are consistent with our main results. Our G portfolios have similar relatively low variances, high expected returns, and high Sharpe ratios. Compared with the VW and EW market portfolios, most differences in variances and Sharpe ratios are significant at the 10% or lower level. G portfolios based on different asset pricing models yield similar results. Again, the G-C4 model underperforms the other G portfolios.

Although results are unchanged for the most part, there are some notable subperiod differences from our earlier results in Table D.5. As shown in Panel C, equal- and value-weighted market portfolios have markedly different variances and expected returns in the most recent subperiod. Conversely, our G portfolios continue to have higher expected returns and lower variances with little or no differences across different asset pricing models. Lastly, our G portfolios have about 80% to 90% lower variances than VW and EW, which is even lower than other sub-periods.

3.5 Conclusion

Previous researchers have explored different methods to estimate the true variance-covariance matrix and expected returns of stocks. Unfortunately, due to estimation errors, the optimal portfolio (with the highest Sharpe ratio) does not perform well in empirical tests. Relevant to the present study, despite similar estimation errors, better performance has been achieved by building global minimum variance portfolios. To explain this disparity, this paper posited that portfolios on the efficient frontier with low variance are less subject to the effects of estimation errors due to the fact that the width of the mean-variance parabola gets wider as total risk increases. According to this logic, the global minimum variance portfolio built using the variance-covariance matrix is likely to underestimate expected returns. Motivated by this insight, we proposed a new method for constructing portfolio G based on a valid asset pricing model. We created a variety of G portfolios using the CAPM market model, Fama and French three-factor model, Carhart four-factor model, and the recently proposed ZCAPM.

Empirical results showed that our new method is able to build global minimum variance portfolios with good performance characteristics. Similar to previous studies, our G portfolios have low variance, which confirms that estimation errors in existing methods have little effect on the variance. However, in contrast to prior methods based on the variance-covariance matrix, our G portfolios have surprisingly high expected returns. Compared with equal and value-weighted market portfolios, G portfolios based on asset pricing models have Sharpe ratios approximately two times higher than these general market indexes in our sample period. While different models generally produce similar results, G portfolio performance tends to diminish in the four-factor model due to numerous factors affecting the sorting process. In general, our findings support the notion that low variance efficient portfolios are less vulnerable to estimation errors. Even for average portfolio turnover, further tests confirm that our results are resilient to transaction costs. Also, tests corroborate that our G portfolios are not materially changed by a few individual stocks or extreme values.

We conclude that asset pricing models can be used to build efficient global minimum variance portfolios. Without requiring the estimation of the variance-covariance matrix, this model-based approach is less prone to estimation errors documented in the literature. Also, our approach works well with large numbers of individual stocks or assets. Further research is ongoing to develop high performing portfolios across a spectrum of different risk levels along the mean-variance efficient frontier.

4. SUMMARY AND CONCLUSIONS

We propose two new empirical methods to be used in finance studies in the dissertation. The first one is applying a short-run event study method to the long-run analysis, allowing risk levels to be dynamically adjusted after major corporate events. The second method uses information from idiosyncratic exposure of individual stocks to estimate the global minimum variance portfolio, avoiding estimation errors coming from estimating the covariance matrix.

In Section 2, we re-examined long-run abnormal returns after major corporate events using our RPE method. There are three main findings. First, risk do shifts around seasoned equity offering (SEOs), merger and acquisitions (M&As), share repurchases (SRs), and stock splits (SPLTs) announcement dates, affecting results of long-run event studies. Second, with appropriate dynamic risk adjustment, abnormal returns are not evident after major corporate events over the five-year, post-event period. Our findings are consistent with the efficient market hypothesis and previous literature such as Fama (1998). Third, the RPE method we propose is a suitable method for future long-run event studies. It controls both Type I and II errors in a reasonable range even when risk is shifting. Also, our RPE method provides results robust to different control groups and asset pricing models being used. Further event studies is recommended using the RPE method for appropriate risk adjustments.

In Section 3, we build new global minimum variance portfolios using a new method purely based on asset pricing models. We posited that it is the expected returns of the portfolio that is mainly affected by estimation errors coming from estimating the covariance matrix. Our new method avoids the use of the covariance matrix and its associated estimation errors. We find that the global minimum variance portfolios we build have low variance comparable with previous studies but with surprisingly high expected returns. Such good performance is not induced by the domination of several individual assets and not canceled by transaction costs. We also find that heavyweights on large stocks could have adverse effects on the expected returns. Finally, we conclude that the new method is suitable to be used for building the global minimum variance portfolio by researchers and practitioners. Further research is ongoing to develop high performing portfolios across a spectrum of different risk levels along the mean-variance efficient frontier.

REFERENCES

Agrawal, A., Jaffe, J. F., Mandelker, G. N., 1992. The post-merger performance of acquiring firms: A re-examination of an anomaly. Journal of Finance 47, 1605–1621.

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. Journal of Financial Markets 5, 31–56.

Ang, A., Hodrick, R. J., Xing, Y., Zhang, X., 2006. The cross-section of volatility and expected returns. Journal of Finance 61, 259–299.

Asquith, P., 1983. Merger bids, uncertainty, and stockholder returns. Journal of Financial Economics 11, 51–83.

Baker, A., 2016. Single-firm event studies, securities fraud, and financial crisis: Problems of inference. Stanford Law Review 68, 1207–1261.

Baker, M., Bradley, B., Wurgler, J., 2011. Benchmarks as limits to arbitrage: Understanding the low-volatility anomaly. Financial Analysts Journal 67, 40–54.

Barber, B. M., Lyon, J. D., 1997. Detecting long-run abnormal stock returns: The empirical power and specification of test statistics. Journal of Financial Economics 43, 341–372.

Barberis, N., Shleifer, A., Vishny, R., 1998. A model of investor sentiment. Journal of Financial Economics 49, 307–343.

Bessembinder, H., Cooper, M. J., Zhang, F., 2019. Characteristic-based benchmark returns and corporate events. The Review of Financial Studies 32, 75–125.

Bessembinder, H., Zhang, F., 2013. Firm characteristics and long-run stock returns after corporate events. Journal of Financial Economics 109, 83–102.

Best, M. J., Grauer, R. R., 1991. On the sensitivity of mean-variance-efficient portfolios to changes in asset means: Some analytical and computational results. The Review of Financial Studies 4, 315–342.

Best, M. J., Grauer, R. R., 1992. Positively weighted minimum-variance portfolios and the structure of asset expected returns. Journal of Financial and Quantitative Analysis 27, 513–537.

Betton, S., Eckbo, B. E., Thorburn, K. S., 2008. Corporate Takeovers, Elsevier, San Diego, book section Chapter 15, pp. 291–429.

Billett, M. T., Flannery, M. J., Garfinkel, J. A., 2011. Frequent issuers' influence on long-run post-issuance returns. Journal of Financial Economics 99, 349–364.

Black, F., Litterman, R., 1992. Global portfolio optimization. Financial Analysts Journal 48, 28–43.

Boehme, R. D., Sorescu, S. M., 2002. The long-run performance following dividend initiations and resumptions: Underreaction or product of chance? Journal of Finance 57, 871–900.

Boehmer, E., Masumeci, J., Poulsen, A. B., 1991. Event-study methodology under conditions of event-induced variance. Journal of Financial Economics 30, 253–272.

Brandt, M. W., 2010. Portfolio Choice Problems, North-Holland, San Diego, vol. 1, book section Chapter 5, pp. 269–336.

Brav, A., 2000. Inference in long-horizon event studies: A bayesian approach with application to initial public offerings. Journal of Finance 55, 1979–2016.

Brav, A., Geczy, C., Gompers, P. A., 2000. Is the abnormal return following equity issuances anomalous? Journal of Financial Economics 56, 209–249.

Brav, A., Gompers, P. A., 1997. Myth or reality? the long-run underperformance of initial public offerings: Evidence from venture and nonventure capital-backed companies. Journal of Finance 52, 1791–1821.

Brown, S. J., Warner, J. B., 1985. Using daily stock returns: The case of event studies. Journal of Financial Economics 14, 3–31.

Byun, J., Rozeff, M. S., 2003. Long-run performance after stock splits: 1927 to 1996. Journal of Finance 58, 1063–1085.

Campbell, J. Y., Lo, A. W., MacKinlay, A. C., 1997. The Econometrics of Financial Markets. Princeton University Press, Princeton.

Carhart, M. M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57–82.

Carlson, M., Fisher, A., Giammarino, R., 2006. Corporate investment and asset price dynamics: Implications for seo event studies and long-run performance. Journal of Finance 61, 1009–1034.

Caton, G. L., Goh, J., Lee, Y. T., Linn, S. C., 2016. Governance and post-repurchase performance. Journal of Corporate Finance 39, 155–173.

Chan, L. K. C., Karceski, J., Lakonishok, J., 1999. On portfolio optimization: Forecasting covariances and choosing the risk model. The Review of Financial Studies 12, 937–974.

Chen, Y., Eaton, G. W., Paye, B. S., 2018. Micro(structure) before macro? the predictive power of aggregate illiquidity for stock returns and economic activity. Journal of Financial Economics 130, 48–73.

Clarke, R. G., de Silva, H., Thorley, S., 2006. Minimum-variance portfolios in the u.s. equity market. The Journal of Portfolio Management 33, 10–24.

Clarke, R. G., de Silva, H., Thorley, S., 2011. Minimum-variance portfolio composition. The Journal of Portfolio Management 37, 31–45.

Cochrane, J. H., 2011. Presidential address: Discount rates. Journal of Finance 66, 1047–1108.

Daniel, K., Hirshleifer, D., Subrahmanyam, A., 1998. Investor psychology and security market under- and overreactions. Journal of Finance 53, 1839–1885.

De Bondt, W. F. M., Thaler, R., 1985. Does the stock market overreact? Journal of Finance 40, 793–805.

DeMiguel, V., Garlappi, L., Nogales, F. J., Uppal, R., 2009a. A generalized approach to portfolio optimization: Improving performance by constraining portfolio norms. Management Science 55, 798–812.

DeMiguel, V., Garlappi, L., Uppal, R., 2009b. Optimal versus naive diversification: How inefficient is the 1/n portfolio strategy? The Review of Financial Studies 22, 1915–1953.

Dimson, E., 1979. Risk measurement when shares are subject to infrequent trading. Journal of Financial Economics 7, 197–226.

Dodd, P., Ruback, R., 1977. Tender offers and stockholder returns: An empirical analysis. Journal of Financial Economics 5, 351–373.

Eckbo, B. E., 1983. Horizontal mergers, collusion, and stockholder wealth. Journal of Financial Economics 11, 241–273.

Eckbo, B. E., Masulis, R. W., Norli, Ã., 2000. Seasoned public offerings: resolution of the 'new issues puzzle'. Journal of Financial Economics 56, 251–291.

Eckbo, B. E., Masulis, R. W., Norli, Ã., 2007. Security Offerings, Elsevier, San Diego, book section Chapter 6, pp. 233–373.

Eckbo, B. E., Norli, Ã., 2005. Liquidity risk, leverage and long-run ipo returns. Journal of Corporate Finance 11, 1–35.

Evgeniou, T., de Fortuny, E. J., Nassuphis, N., Vermaelen, T., 2018. Volatility and the buyback anomaly. Journal of Corporate Finance 49, 32–53.

Fama, E. F., 1968. Risk, return and equilibrium: Some clarifying comments. Journal of Finance 23, 29–40.

Fama, E. F., 1998. Market efficiency, long-term returns, and behavioral finance. Journal of Financial Economics 49, 283–306.

Fama, E. F., Fisher, L., Jensen, M. C., Roll, R., 1969. The adjustment of stock prices to new information. International Economic Review 10, 1–21.

Fama, E. F., French, K. R., 1992. The cross-section of expected stock returns. Journal of Finance 47, 427–465.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fama, E. F., French, K. R., 2015. A five-factor asset pricing model. Journal of Financial Economics 116, 1–22.

Fama, E. F., French, K. R., 2018. Choosing factors. Journal of Financial Economics 128, 234–252.

Fama, E. F., French, K. R., 2020. Comparing cross-section and time-series factor models. The Review of Financial Studies 33, 1891–1926.

Ferson, W., 2019. Empirical Asset Pricing: Models and Methods. MIT Press, Cambridge.

Frost, P. A., Savarino, J. E., 1986. An empirical bayes approach to efficient portfolio selection. Journal of Financial and Quantitative Analysis 21, 293–305.

Frost, P. A., Savarino, J. E., 1988. For better performance: Constrain portfolio weights. The Journal of Portfolio Management 15, 29–34.

Fu, F., Huang, S., 2015. The persistence of long-run abnormal returns following stock repurchases and offerings. Management Science 62, 964–984.

Garlappi, L., Uppal, R., Wang, T., 2007. Portfolio selection with parameter and model uncertainty: A multi-prior approach. The Review of Financial Studies 20, 41–81.

Gompers, P. A., 2015. Testimony in carpenters pension trust fund of st. louis versus barclays plc, et al. United States Court of Appeals for the Second Circuit, New York, NY. pp. 1–1073.

Gompers, P. A., Lerner, J., 2003. The really long-run performance of initial public offerings: The pre-nasdaq evidence. Journal of Finance 58, 1355–1392.

Green, R. C., Hollifield, B., 1992. When will mean-variance efficient portfolios be well diversified? Journal of Finance 47, 1785–1809.

Grullon, G., Michaely, R., Swaminathan, B., 2002. Are dividend changes a sign of firm maturity? The Journal of Business 75, 387–424.

Haugen, R. A., Baker, N. L., 1991. The efficient market inefficiency of capitalization-weighted stock portfolios. The Journal of Portfolio Management 17, 35–40.

Haugen, R. A., Baker, N. L., 2012. Low risk stocks outperform within all observable markets of the world. working paper. Available at SSRN Electronic Journal 2055431 .

How, J. C., Ngo, K., Verhoeven, P., 2011. Dividend initiations and long-run ipo performance. Australian Journal of Management 36, 267–286.

Huang, R., Ritter, J., 2020. The puzzle of frequent and large issues of debt and equity. Journal of Financial and Quantitative Analysis p. Forthcoming.

Ibbotson, R. G., 1975. Price performance of common stock new issues. Journal of Financial Economics 2, 235–272.

Ikenberry, D., Lakonishok, J., Vermaelen, T., 1995. Market underreaction to open market share repurchases. Journal of Financial Economics 39, 181–208.

Jagannathan, R., Ma, T., 2003. Risk reduction in large portfolios: Why imposing the wrong constraints helps. Journal of Finance 58, 1651–1683.

Jegadeesh, N., Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. Journal of Finance 48, 65–91.

Jensen, M. C., 1968. The performance of mutual funds in the period 1945-1964. Journal of Finance 23, 389–416.

Jobson, J. D., Korkie, B., 1980. Estimation for markowitz efficient portfolios. Journal of the American Statistical Association 75, 544–554.

Jobson, J. D., Korkie, B. M., 1981a. Performance hypothesis testing with the sharpe and treynor measures. Journal of Finance 36, 889–908.

Jobson, J. D., Korkie, R. M., 1981b. Putting markowitz theory to work. The Journal of Portfolio Management 7, 70–74.

Jorion, P., 1985. International portfolio diversification with estimation risk. The Journal of Business 58, 259–278.

Jorion, P., 1986. Bayes-stein estimation for portfolio analysis. Journal of Financial and Quantitative Analysis 21, 279–292.

Jorion, P., 1991. Bayesian and capm estimators of the means: Implications for portfolio selection. Journal of Banking & Finance 15, 717–727.

Kahneman, D., Tversky, A., 1982. Intuitive predictions: Biases and corrective procedures, Cambridge University Press, Cambridge, England.

Kan, R., Zhou, G., 2007. Optimal portfolio choice with parameter uncertainty. Journal of Financial and Quantitative Analysis 42, 621–656.

Kolari, J. W., Pynnonen, S., 2010. Event study testing with cross-sectional correlation of abnormal returns. The Review of Financial Studies 23, 3996–4025.

Kolari, J. W., Pynnonen, S., Tuncez, A. M., 2021. On long-run stock returns after corporate events. Critical Finance Review 10, Forthcoming.

Kothari, S. P., Warner, J. B., 2007. Econometrics of Event Studies, Elsevier, San Diego, book section Chapter 1, pp. 3–36.

Ledoit, O., Wolf, M., 2004. Honey, i shrunk the sample covariance matrix. The Journal of Portfolio Management 30, 110–119.

Ledoit, O., Wolf, M., 2008. Robust performance hypothesis testing with the sharpe ratio. Journal of Empirical Finance 15, 850–859.

Ledoit, O., Wolf, M., 2011. Robust performances hypothesis testing with the variance. Wilmott 2011, 86–89.

Ledoit, O., Wolf, M., 2020. The power of (non-)linear shrinking: A review and guide to covariance matrix estimation. Journal of Financial Econometrics p. nbaa007.

Lee, E., Strong, N., Zhu, Z., 2014. Did regulation fair disclosure, sox, and other analyst regulations reduce security mispricing? Journal of Accounting Research 52, 733–774.

Lesmond, D. A., Ogden, J. P., Trzcinka, C. A., 1999. A new estimate of transaction costs. The Review of Financial Studies 12, 1113–1141.

Lewellen, J., Nagel, S., 2006. The conditional capm does not explain asset-pricing anomalies. Journal of Financial Economics 82, 289–314.

Li, E. X. N., Livdan, D., Zhang, L., 2009. Anomalies. The Review of Financial Studies 22, 4301–4334.

Liu, W., Kolari, J. W., Huang, J., 2019. A new investment technology: The zcapm. working paper. Available at SSRN Electronic Journal 2885467 .

Loughran, T., Ritter, J. R., 1995. The new issues puzzle. Journal of Finance 50, 23–51.

Loughran, T., Ritter, J. R., 2000. Uniformly least powerful tests of market efficiency. Journal of Financial Economics 55, 361–389.

Loughran, T., Vijh, A. M., 1997. Do long-term shareholders benefit from corporate acquisitions? Journal of Finance 52, 1765–1790.

Lyandres, E., Sun, L., Zhang, L., 2008. The new issues puzzle: Testing the investment-based explanation. The Review of Financial Studies 21, 2825–2855.

Lyon, J. D., Barber, B. M., Tsai, C.-L., 1999. Improved methods for tests of long-run abnormal stock returns. Journal of Finance 54, 165–201.

Maillet, B., Tokpavi, S., Vaucher, B., 2015. Global minimum variance portfolio optimisation under some model risk: A robust regression-based approach. European Journal of Operational Research 244, 289–299.

Malmendier, U., Moretti, E., Peters, F. S., 2018. Winning by losing: Evidence on the long-run effects of mergers. The Review of Financial Studies 31, 3212–3264.

Markowitz, H., 1952. Portfolio selection. Journal of Finance 7, 77–91.

Markowitz, H., 1959. Portfolio Selection: Efficient Diversification of Investments (Cowles Foundation Monograph: No. 16). Wiley, New York.

Memmel, C., 2003. Performance hypothesis testing with the sharpe ratio. Finance Letters 1, 21–23.

Merton, R. C., 1972. An analytic derivation of the efficient portfolio frontier. Journal of Financial and Quantitative Analysis 7, 1851–1872.

Merton, R. C., 1980. On estimating the expected return on the market: An exploratory investigation. Journal of Financial Economics 8, 323–361.

Michaely, R., Thaler, R. H., Womack, K. L., 1995. Price reactions to dividend initiations and omissions: Overreaction or drift? Journal of Finance 50, 573–608.

Michaud, R. O., 1989. The markowitz optimization enigma: Is 'optimized' optimal? Financial Analysts Journal 45, 31–42.

Mitchell, M. L., Stafford, E., 2000. Managerial decisions and long-term stock price performance. The Journal of Business 73, 287–329.

Pástor, L., 2000. Portfolio selection and asset pricing models. Journal of Finance 55, 179–223.

Pástor, L., Stambaugh, R. F., 2000. Comparing asset pricing models: an investment perspective. Journal of Financial Economics 56, 335–381.

Pynnonen, S., 2005. On regression based event study. Acta Wasaensia 143, 327–354.

Ritter, J., 1991. The long-run performance of initial public offerings. Journal of Finance 46, 3–27.

Salinger, M., 1992. Value event studies. The Review of Economics and Statistics 74, 671–677.

Scholes, M., Williams, J., 1977. Estimating betas from nonsynchronous data. Journal of Financial Economics 5, 309–327.

Sehgal, S., Banerjee, S., Deisting, F., 2012. The impact of m&a announcement and financing strategy on stock returns: Evidence from bricks markets. International Journal of Economics and Finance 4, 76–90.

Sharpe, W. F., 1963. A simplified model for portfolio analysis. Management Science 9, 277–293.

Sharpe, W. F., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. Journal of Finance 19, 425–442.

Spiess, D. K., Affleck-Graves, J., 1995. Underperformance in long-run stock returns following seasoned equity offerings. Journal of Financial Economics 38, 243–267.

APPENDIX A

DEALING WITH NON-SYNCHRONOUS TRADING

As brought out by Scholes and Williams (1977) and Dimson (1979), non-synchronous trading could introduce biased and inconsistent estimation of $beta$ using daily stock returns. Highly frequent trading will have upward biased $beta$ while infrequent trading will induce downward bias. Such bias might result in misspecification of short-run event study method which also makes our RPE method invalid. Simulation tests in Brown and Warner (1985) show that although estimated $beta$ are biased, short-run event study method is still robust using OLS market model. They argue that biased in estimated $beta$ are mainly compensated by a bias in $alpha$ due to the fact that OLS residuals for a stock is constructed to sum to zero. While estimated $alpha$ will be deducted to calculate abnormal return, event study method will not be misspecified. Following Scholes and Williams (1977) , Dimson (1979) and Brown and Warner (1985), we repeat most of our analysis using Dimson aggregated coefficients with three leads and lags. Using CAPM market model with 252 days estimation window as an example, the abnormal return for each event day(T) is calculated as following:

$$R_{it} - R_{ft} = \alpha_i + b_{ik}(R_{m(t+k)} - R_{f(t+k)}) + e_{it}, \tag{A.1}$$

$$\hat{b_i} = \sum_{k=-3}^{t=3} b_{ik}, \tag{A.2}$$

$$\hat{\alpha_i} = \frac{1}{252} \sum_{t=-252}^{t=-1} (R_{it} - R_{ft}) - \hat{b_i} \frac{1}{252} \sum_{t=-252}^{t=-1} (R_{mt} - R_{ft}), \tag{A.3}$$

$$AR_{iT} = [R_{iT} - R_{fT}] - [\hat{\alpha}_i + \hat{b}_i(R_{mT} - R_{fT})]. \tag{A.4}$$

all notations follows main paper. Different models with different estimation windows are applied to the same process.

We provide some main results using CAPM market model, Fama and French five-factor model, and Fama and French five-factor plus momentum model in table B.25 and B.26 in the Appendix B. Unreported results do show that Dimson's method does result in different estimated $betas$, which is consistent with previous literatures. On the other hand, results in Table B.25 and B.26 does indicate that our main results are not affected by non-synchronous trading. We still find no long-term abnormal returns after major corporate events (stock repurchase and splits results are not reported but similar to those in the main paper). All findings here are consistent with findings in Brown and Warner (1985).

APPENDIX B

TABLES FOR SECTION 2

This appendix presents tables for Section 2. First, the number of different events before and after overlapping filter are summarized in Table B.1. Then, abnormal returns for SEOs and M&As are reported in Table B.2 to Table B.5. Results for formal risk shifting tests are reported in Table B.6. Using straddle estimation windows, long-run abnormal returns are reported in Table B.8, Table B.9, and Table B.11. Comparative analysis using other methods are presented in Table B.10. Table B.11 shows our simulation results using SEO data.

Other robustness tests of abnormal returns using different asset pricing models and events are presented in Tables B.12 to B.16. Subperiods results for 1980-1997 and 1998-2015 are in Tables B.17 to B.24. Finally, abnormal returns using Dimson Aggregated betas are stored in Table B.25 and B.26.

Table B.1: Number of seasoned equity offerings (SEOs), mergers and acquistions (M&As), stock repurchases (SRs), and stock split (SPLTs) from 1980 to 2015

This table summarizes annual seasoned equity offerings (SEOs), mergers and acquistions (M&As), stock repurchases (SRs), and stock split (SPLTs) from 1980 to 2015. Data is downloaded from Thomson ONE (SDC) and CRSP database. Total samples of SEOs, M&As, SRs, and SPLTs are shown in parentheses. The final sample drops overlapping events with a five-year, post-event window for SEOs, M&As, SRs, and SPLTs.

Year	SEO	M&A	REP	SPLT
1980	73 (116)	4 (5)	1 (1)	138 (199)
1981	76 (130)	8 (10)	8 (9)	136 (216)
1982	69 (149)	1 (1)	18 (23)	30 (70)
1983	211 (349)	1 (2)	88 (115)	190 (346)
1984	42 (96)	18 (27)	276 (376)	74 (130)
1985	78 (136)	66 (98)	32 (68)	81 (155)
1986	111 (201)	71 (110)	28 (65)	123 (275)
1987	58 (152)	69 (120)	37 (99)	121 (219)
1988	32 (71)	44 (94)	25 (87)	27 (57)
1989	46 (100)	56 (107)	46 (154)	59 (108)
1990	41 (98)	42 (71)	276 (669)	38 (93)
1991	91 (201)	43 (101)	63 (271)	41 (91)
1992	85 (197)	74 (141)	104 (400)	88 (171)
1993	111 (254)	83 (179)	73 (388)	93 (172)
1994	88 (215)	121 (246)	166 (731)	70 (143)
1995	138 (283)	150 (312)	150 (800)	92 (183)
1996	152 (332)	144 (310)	185 (988)	114 (220)
1997	131 (306)	172 (374)	220 (930)	132 (232)
1998	102 (212)	186 (371)	405 (1356)	124 (230)
1999	82 (215)	146 (295)	300 (1047)	74 (180)
2000	76 (241)	132 (297)	109 (530)	79 (194)
2001	93 (235)	101 (205)	147 (521)	27 (69)
2002	92 (212)	69 (147)	85 (372)	38 (87)
2003	71 (226)	85 (175)	58 (375)	46 (84)
2004	119 (292)	86 (181)	79 (447)	71 (130)
2005	66 (214)	92 (199)	108 (514)	83 (147)
2006	68 (219)	103 (192)	98 (491)	71 (117)
2007	75 (217)	119 (189)	175 (736)	54 (80)
2008	28 (120)	71 (137)	181 (787)	15 (28)
2009	81 (239)	58 (100)	48 (306)	4 (7)
2010	53 (184)	50 (94)	61 (424)	9 (16)
2011	50 (198)	47 (98)	89 (587)	27 (40)
2012	32 (168)	60 (117)	60 (407)	18 (29)
2013	68 (212)	67 (124)	69 (378)	26 (32)
2014	53 (221)	121 (167)	149 (471)	31 (35)
2015	136 (316)	126 (196)	171 (468)	11 (17)
Total	2,978 (7,327)	2,886 (5,592)	4,188 (16,391)	2455 (4602)

Table B.2: Fama and French five-factor plus momentum model abnormal returns after seasoned equity offerings (SEOs): Matched samples for controls

This table reports average abnormal returns after seasoned equity offerings (SEOs) based on estimates from the five-factor plus momentum model. The sample period covers events from January 1980 to December 2015. Results are shown for SEO stocks (Panel A), matched control stocks (Panel B), and differences between SEOs stocks and matched control stocks (Panels C and D). The model is estimated 1 year, 3 months, and 2 months before day T as well as 2 months after day T, where $T = 0, ..., L$. Beginning with day 0, the model is fitted in the estimation period for each stock, and $\hat{AR}_{i0}$ is computed as the forecast error on day 0. The entire process is rolled forward one day at time to create a daily time series $\hat{AR}_{i0}...\hat{AR}_{iT}$ beginning with the event announcement on day 0 and ending on the last day of the five-year, post-event period denoted day L. Abnormal returns are averaged on each day t across sample stocks. The mean $\hat{AR}$s (in percent,compounded monthly) in one year as well as quarterly increments after the event day and associated cross-correlation robust t-statistics († and ‡ for 5% and 1% significance level separately) are reported.

	Model Estimation Window							
	1 Year Before		3 Months Before		2 Months Before		2 Months After	
Post-Event Period	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t
Panel A: SEO stocks								
Year 1	-1.919‡	-17.85	-0.330‡	-3.53	-0.224†	-2.44	0.275†	2.20
Year 2	-0.053	-1.27	-0.184†	-2.28	-0.282‡	-3.02	0.109	0.31
Year 3	0.227	1.35	-0.010	-0.74	-0.106	-1.44	0.006	0.37
Year 4	0.027	0.18	-0.061	-1.07	-0.120	-1.38	0.055	0.10
Year 5	0.047	0.13	-0.148	-1.37	-0.098	-0.92	0.129	0.71
Panel B: Matched control stocks								
Year 1	-0.234‡	-2.74	-0.172†	-2.11	-0.172†	-1.99	0.034	0.03
Year 2	-0.045	-1.12	-0.141	-1.72	-0.170	-1.90	0.088	0.34
Year 3	0.052	0.15	-0.104	-0.93	-0.143	-1.16	0.000	0.00
Year 4	-0.091	-1.06	-0.227	-1.98	-0.288†	-2.17	0.016	0.98
Year 5	0.009	0.46	-0.062	-0.75	-0.052	-0.73	0.047	0.91
Panel C: SEO minus matched control stocks								
Year 1	-1.688‡	-10.97	-0.158	-0.98	-0.052	-0.25	0.241†	2.13
Year 2	-0.008	-0.40	-0.043	-0.44	-0.113	-0.75	0.021	0.09
Year 3	0.175	0.68	0.094	0.08	0.037	0.15	0.006	0.71
Year 4	0.118	0.69	0.166	0.40	0.169	0.31	0.039	0.28
Year 5	0.037	0.05	-0.086	-0.33	-0.046	-0.15	0.083	0.80
Panel D: SEO minus matched control stocks								
Quarter 1	-2.116‡	-6.87	-0.268	-0.70	0.062	0.27	1.024‡	3.12
Quarter 2	-2.395‡	-8.09	-0.319	-1.03	-0.356	-1.06	0.261	1.08
Quarter 3	-1.900‡	-6.04	-0.282	-0.77	-0.140	-0.39	-0.051	-0.35
Quarter 4	-0.329	-1.37	0.240	0.57	0.228	0.70	-0.265	-0.24

Table B.3: Fama and French five-factor plus momentum model abnormal returns after mergers and acquisitions (M&As): Matched samples for controls

This table reports average abnormal returns after mergers and acquisitions (M&As) based on estimates from the five-factor plus momentum model. The sample period covers events from January 1980 to December 2015. Results are shown for M&A stocks (Panel A), matched control stocks (Panel B), and differences between M&A stocks and matched control stocks (Panels C and D). The model is estimated 1 year, 3 months, and 2 months before event day T as well as 2 months after day T, where $T = 0, ..., L$. Beginning with day 0, the model is fitted in the estimation period for each stock, and $\hat{AR}_{i0}$ is computed as the forecast error on day 0. The entire process is rolled forward one day at time to create a daily time series $\hat{AR}_{i0}...\hat{AR}_{iL}$ beginning with the event announcement on day 0 and ending on the last day of the five-year, post-event period denoted day L. Abnormal returns are averaged on each day T across sample stocks. The mean $\hat{AR}$s (in percent, compounded monthly) in one year as well as quarterly increments after the event day and associated cross-correlation robust t-statistics († and ‡ for 5% and 1% significance level separately) are reported.

	Model Estimation Window							
	1 Year Before		3 Months Before		2 Months Before		2 Months After	
Post-Event Period	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t
Panel A: M&A stocks								
Year 1	-0.890‡	-8.39	-0.695‡	-4.76	-0.664‡	-4.55	0.158	1.60
Year 2	-0.070	-1.21	-0.073	-1.72	-0.080	-1.84	0.070	0.61
Year 3	0.144	0.53	-0.113	-1.42	-0.113	-1.70	0.088	0.14
Year 4	-0.117	-0.28	-0.284	-1.35	-0.436‡	-2.77	0.126	1.02
Year 5	0.043	0.12	-0.069	-1.10	-0.118	-1.84	0.050	0.81
Panel B: Matched control stocks								
Year 1	-0.052	-0.74	-0.071	-0.79	-0.127	-1.61	0.006	0.17
Year 2	0.038	0.08	-0.045	-0.66	-0.138	-1.53	-0.026	-0.27
Year 3	-0.191	-1.36	-0.292	-1.95	-0.268†	-2.22	0.068	0.36
Year 4	-0.023	-0.44	-0.124	-1.13	-0.140	-1.44	0.136	1.14
Year 5	0.057	0.16	0.062	0.20	-0.008	-0.43	-0.038	-0.03
Panel C: M&A minus matched control stocks								
Year 1	-0.838‡	-5.36	-0.624‡	-2.77	-0.538†	-2.07	0.151	0.99
Year 2	-0.107	-1.07	-0.028	-0.80	0.058	0.30	0.095	0.19
Year 3	0.335	0.90	0.180	0.36	0.155	0.23	0.020	0.06
Year 4	-0.094	-0.14	-0.160	-0.44	-0.297	-1.25	-0.009	-0.02
Year 5	-0.014	-0.54	-0.131	-1.08	-0.111	-0.94	0.089	1.15
Panel D: M&A minus matched control stocks								
Quarter 1	-0.727†	-2.47	-1.183‡	-4.02	-0.876‡	-2.96	0.357	1.34
Quarter 2	-0.845†	-2.57	-0.065	-0.08	-0.040	-0.09	0.145	1.02
Quarter 3	-0.998‡	-3.19	-1.065	-1.18	-1.216	-1.31	0.176	0.46
Quarter 4	-0.781‡	-2.64	-0.179	-0.44	-0.013	0.00	-0.071	-0.82

Table B.4: Fama and French five-factor plus momentum model abnormal returns after seasoned equity offerings (SEOs): Random samples for controls

This table reports average abnormal returns after seasoned equity offerings (SEOs) based on estimates from the five-factor plus momentum model. The sample period covers events from January 1980 to December 2015. Results are shown for SEO stocks (Panel A), random control stocks (Panel B), and differences between SEO stocks and random control stocks (Panels C and D). The model is estimated 1 year, 3 months, and 2 months before event day T as well as 2 months after day T, where $T = 0, ..., L$. Beginning with day 0, the model is fitted in the estimation period for each stock, and $\hat{AR}_{i0}$ is computed as the forecast error on day 0. The entire process is rolled forward one day at time to create a daily time series $\hat{AR}_{i0}...\hat{AR}_{iL}$ beginning with the event announcement on day 0 and ending on the last day of the five-year, post-event period denoted day L. Abnormal returns are averaged on each day T across sample stocks. The mean $\hat{AR}$s (in percent, compounded monthly) in one year as well as quarterly increments after the event day and associated cross-correlation robust t-statistics († and ‡ for 5% and 1% significance level separately) are reported.

	Model Estimation Window							
	1 Year Before		3 Months Before		2 Months Before		2 Months After	
Post-Event Period	$\hat{AR}$(%)	t	$\hat{AR}$(%)	t	$\hat{AR}$(%)	t	$\hat{AR}$(%)	t
Panel A: SEO stocks								
Year 1	-1.919‡	-17.85	-0.330‡	-3.53	-0.224†	-2.44	0.275†	2.20
Year 2	-0.053	-1.27	-0.184†	-2.28	-0.282‡	-3.02	0.109	0.31
Year 3	0.227	1.35	-0.010	-0.74	-0.106	-1.44	0.006	0.37
Year 4	0.027	0.18	-0.061	-1.07	-0.120	-1.38	0.055	0.10
Year 5	0.047	0.13	-0.148	-1.37	-0.098	-0.92	0.129	0.71
Panel B: Random sample control stocks								
Year 1	-0.100	-1.90	-0.020	-0.39	-0.024	-0.42	0.049	0.93
Year 2	-0.124†	-2.05	-0.115	-1.90	-0.102	-1.71	0.139	1.90
Year 3	0.023	0.46	0.003	0.12	0.012	0.12	0.023	0.62
Year 4	-0.046	-0.69	-0.045	-0.55	-0.004	-0.12	0.038	0.24
Year 5	0.035	0.40	-0.012	-0.14	-0.031	-0.35	0.027	0.17
Panel C: SEO minus matched control stocks								
Year 1	-1.821‡	-14.63	-0.310‡	-2.88	-0.200	-1.93	0.226	1.84
Year 2	0.072	0.30	-0.069	-1.02	-0.181	-1.85	-0.029	-0.71
Year 3	0.204	0.98	-0.013	-0.68	-0.118	-1.34	-0.017	-0.25
Year 4	0.074	0.03	-0.015	-0.63	-0.116	-1.15	0.017	0.31
Year 5	0.011	0.24	-0.135	-1.20	-0.066	-0.79	0.102	0.27
Panel D: SEO minus matched control stocks								
Quarter 1	-2.409‡	-10.40	-0.503†	-2.18	-0.153	-0.74	0.930‡	3.58
Quarter 2	-2.754‡	-11.87	-0.528†	-2.26	-0.341	-1.46	0.122	0.60
Quarter 3	-1.754‡	-7.12	-0.263	-0.96	-0.278	-0.97	0.106	0.81
Quarter 4	-0.349†	-2.21	0.057	0.71	-0.027	-0.72	-0.250	-0.84

Table B.5: Fama and French five-factor plus momentum model abnormal returns after mergers and acquisitions (M&As): Random samples for controls

This table reports average abnormal returns after mergers and acquisitions (M&As) based on estimates from the five-factor plus momentum model. The sample period covers events from January 1980 to December 2015. Results are shown for M&A stocks (Panel A), random control stocks (Panel B), and differences between M&A stocks and random control stocks (Panels C and D). The model is estimated 1 year, 3 months, and 2 months before event day T as well as 2 months after day T, where $T = 0, ..., L$. Beginning with day 0, the model is fitted in the estimation period for each stock, and $\hat{AR}_{i0}$ is computed as the forecast error on day 0. The entire process is rolled forward one day at time to create a daily time series $\hat{AR}_{i0}...\hat{AR}_{iL}$ beginning with the event announcement on day 0 and ending on the last day of the five-year, post-event period denoted day L. Abnormal returns are averaged on each event day T across sample stocks. The mean $\hat{AR}$s (in percent, compounded monthly) in one year as well as quarterly increments after the event day and associated cross-correlation robust t-statistics († and ‡ for 5% and 1% significance level separately) are reported.

	Model Estimation Window							
	1 Year Before		3 Months Before		2 Months Before		2 Months After	
Post-Event Period	$\hat{AR}$(%)	t	$\hat{AR}$(%)	t	$\hat{AR}$(%)	t	$\hat{AR}$(%)	t
Panel A: M&A stocks								
Year 1	-0.890‡	-8.39	-0.695‡	-4.76	-0.664‡	-4.55	0.158	1.60
Year 2	-0.070	-1.21	-0.073	-1.72	-0.080	-1.84	0.070	0.61
Year 3	0.144	0.53	-0.113	-1.42	-0.113	-1.70	0.088	0.14
Year 4	-0.117	-0.28	-0.284	-1.35	-0.436	-2.77	0.126	1.02
Year 5	0.043	0.12	-0.069	-1.10	-0.118	-1.84	0.050	0.81
Panel B: Random sample control stocks								
Year 1	-0.144†	-2.09	-0.084	-1.17	-0.092	-1.24	0.044	0.68
Year 2	0.022	0.34	-0.029	-0.32	-0.050	-0.56	0.072	0.35
Year 3	-0.043	-0.63	-0.090	-1.17	-0.055	-0.71	0.093	1.13
Year 4	-0.039	-0.51	-0.042	-0.49	-0.059	-0.66	0.062	0.33
Year 5	-0.134	-1.56	-0.092	-1.06	-0.061	-0.68	0.089	0.41
Panel C: M&A minus matched control stocks								
Year 1	-0.746‡	-5.74	-0.612‡	-3.42	-0.572‡	-3.24	0.114	1.06
Year 2	-0.091	-1.22	-0.044	-1.54	-0.030	-1.57	-0.003	-0.66
Year 3	0.187	0.67	-0.023	-0.53	-0.058	-0.91	-0.005	-0.24
Year 4	-0.077	-0.46	-0.242	-1.04	-0.377†	-2.12	0.064	0.34
Year 5	0.178	1.26	0.022	0.00	-0.058	-0.91	-0.039	-1.22
Panel D: M&A minus matched control stocks								
Quarter 1	-0.661‡	-2.87	-1.191‡	-4.97	-0.993‡	-4.25	0.386	1.49
Quarter 2	-0.756‡	-3.11	-0.047	-0.33	-0.049	-0.53	-0.029	-0.20
Quarter 3	-0.832‡	-3.14	-1.039	-1.20	-1.160	-1.64	0.122	0.62
Quarter 4	-0.735‡	-3.02	-0.166	-0.68	-0.080	-0.39	-0.022	-0.07

Table B.6: Risk shifts before and after SEO and M&A event day based on the CAPM market model using different estimaton windows

Based on the sample period 1980 to 2015, this table reports risk shift tests of the CAPM market model for seasoned equity offerings (SEOs in Panels A and B) and mergers and acquisitions (M&As in Panels C and D). Different before and after event estimation windows are used. The regression model is:

$$(R_{it} - R_{ft}) = \hat{\alpha}_i + \hat{\alpha}'_i D_{it} + \hat{b}_i(R_{mt} - R_{ft}) + \hat{b}'_i D_{it}(R_{mt} - R_{ft}) + e_{it},$$

where R_{it} is the daily return for the ith SEO or M&A stock, R_{mt} is the daily return on the value-weighted market index, R_{ft} is the daily return on one-month U.S. Treasury bills, D_{it} equals 0 in pre-event days and 1 in post-event days, and e_{it} is a white noise error term. Estimated coefficients are averaged across event stocks on event day (and standard t-tests in parentheses) are estimated. If the mean coefficient $\hat{\bar{b}}'_i$ does not equal zero, we infer that average beta risk shifted among sample stocks.

Panel A: SEO stocks				
Estimation period	$\hat{\bar{\alpha}}$	$\hat{\bar{\alpha}}'$	$\hat{\bar{b}}$	$\hat{\bar{b}}'_i$
15 days before and after	0.04†	0.09‡	0.98‡	0.03
	(2.09)	(3.48)	(31.05)	(0.84)
25 days before and after	0.09‡	0.00	0.99‡	0.04
	(6.10)	(0.12)	(39.25)	(1.25)
42 days before and after	0.13‡	-0.08‡	0.98‡	0.09‡
	(11.54)	(-5.12)	(49.07)	(3.73)
60 days before and after	0.16‡	-0.14‡	0.98‡	0.10‡
	(17.40)	(-10.46)	(56.54)	(4.89)
90 days before and after	0.20‡	-0.20‡	0.99‡	0.09‡
	(20.29)	(-15.23)	(64.99)	(5.09)
Panel B: SEO stocks minus matched control stocks				
Estimation period	$\hat{\bar{\alpha}}$	$\hat{\bar{\alpha}}'$	$\hat{\bar{b}}$	$\hat{\bar{b}}'_i$
15 days before and after	-0.02	0.11‡	0.22‡	0.03
	(-0.79)	(2.67)	(4.68)	(0.47)
25 days before and after	0.03	0.02	0.21‡	0.04
	(1.56)	(0.67)	(5.42)	(0.91)
42 days before and after	0.05‡	-0.05†	0.19‡	0.07†
	(3.32)	(-2.24)	(6.69)	(2.05)
60 days before and after	0.09‡	-0.11‡	0.19‡	0.07†
	(7.12)	(-5.96)	(8.12)	(2.28)
90 days before and after	0.12‡	-0.16‡	0.18‡	0.08‡
	(10.05)	(-9.64)	(9.26)	(3.44)

Table B.6 continued:

Panel C: M&A stocks				
Estimation period	$\hat{\bar{\alpha}}$	$\hat{\bar{\alpha}}'$	$\hat{\bar{b}}$	$\hat{\bar{b}}'_i$
15 days before and after	0.14‡	-0.06†	0.85‡	-0.08†
	(7.99)	(-2.18)	(29.69)	(-2.08)
25 days before and after	0.10‡	-0.04†	1.22‡	-0.07‡
	(5.72)	(-2.09)	(42.62)	(-3.28)
42 days before and after	0.10‡	-0.07‡	0.86‡	-0.04
	(10.48)	(-4.94)	(47.59)	(-1.85)
60 days before and after	0.10‡	-0.07‡	0.86‡	-0.03
	(11.70)	(-6.42)	(52.19)	(-1.55)
90 days before and after	0.09‡	-0.07‡	0.85‡	-0.01
	(12.54)	(-6.95)	(58.22)	(-0.54)
Panel D: M&A stocks minus matched control stocks				
Estimation period	$\hat{\bar{\alpha}}$	$\hat{\bar{\alpha}}'$	$\hat{\bar{b}}$	$\hat{\bar{b}}'_i$
15 days before and after	0.10‡	-0.04	0.09†	-0.12
	(4.44)	(-1.04)	(2.29)	(-1.77)
25 days before and after	0.09‡	-0.05	0.06	-0.02
	(5.09)	(-1.76)	(1.99)	(-0.30)
42 days before and after	0.07‡	-0.05†	0.05†	-0.06
	(5.16)	(-2.46)	(2.05)	(-1.22)
60 days before and after	0.06‡	-0.06‡	0.06‡	-0.05
	(5.47)	(-3.16)	(2.72)	(-1.19)
90 days before and after	0.04‡	-0.05‡	0.04†	-0.03
	(4.43)	(-2.65)	(2.34)	(-0.83)

Table B.7: CAPM market model and Fama and French five-factor plus momentum model abnormal returns based on straddled event days with an estimation window two months before and after event day T for seasoned equity offerings (SEOs): Matched and random samples for controls

This table reports average abnormal returns after seasoned equity offerings (SEOs) based on estimates from the CAPM market model and five-factor plus momentum (denoted FF5+Mom) model. The sample period covers events from January 1980 to December 2015. Results are shown for SEO stocks (Panel A), control stocks (Panel B), and differences between SEO stocks and both matched and random control stocks (Panels C and D). The model is estimated using returns 2 months before event day T as well as 2 months after day T (i.e., $T = 0, ..., L$). Beginning with day 0, the model is fitted in the estimation period for each stock, and $\hat{AR}_{i0}$ is computed as the forecast error on day 0. The entire process is rolled forward one day at time to create a daily time series $\hat{AR}_{i0}...\hat{AR}_{iL}$ beginning with the event announcement on day 0 and ending on the last day of the five-year, post-event period denoted day L. Abnormal returns are averaged on each day T across sample stocks. The mean $\hat{AR}$s (in percent, compounded monthly) in one year as well as quarterly increments after the event day and associated cross-correlation robust t-statistics († and ‡ for 5% and 1% significance level separately) are reported.

	Market Model Matched Control		Market Model Random Control		FF5+Mom Matched Control		FF5+Mom Random Control	
Post-Event Period	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t
Panel A: SEO stocks								
Year 1	0.011	0.15	0.011	0.15	0.083	0.30	0.083	0.30
Year 2	-0.038	-0.75	-0.038	-0.75	-0.036	-1.08	-0.036	-1.08
Year 3	-0.038	-0.44	-0.038	-0.44	-0.040	-0.67	-0.040	-0.67
Year 4	-0.052	-1.02	-0.052	-1.02	-0.024	-1.15	-0.024	-1.15
Year 5	-0.050	-0.37	-0.050	-0.37	-0.006	-0.39	-0.006	-0.39
Panel B: Control stocks								
Year 1	-0.048	-0.82	-0.013	-0.15	-0.002	-0.66	0.022	0.37
Year 2	-0.028	-0.62	-0.001	-0.05	0.007	0.53	0.027	0.34
Year 3	-0.031	-0.63	-0.008	-0.05	-0.024	-0.66	0.001	0.04
Year 4	-0.017	-0.37	-0.009	-0.11	-0.039	-0.62	0.036	0.50
Year 5	-0.071	-0.51	-0.011	-0.02	0.094	0.54	0.009	0.40
Panel C: SEO minus control stocks								
Year 1	0.060	0.77	0.024	0.15	0.084	0.86	0.060	0.16
Year 2	-0.010	-0.18	-0.037	-0.71	-0.044	-0.35	-0.064	-1.03
Year 3	-0.007	-0.19	-0.031	-0.40	-0.016	-0.05	-0.041	-0.57
Year 4	-0.036	-0.52	-0.044	-1.05	0.016	0.42	-0.060	-1.33
Year 5	0.022	0.44	-0.039	-0.29	-0.099	-0.47	-0.015	-0.46
Panel D: SEO minus control stocks								
Quarter 1	0.266	1.24	0.185	0.67	0.457	1.78	0.412	1.69
Quarter 2	0.021	0.35	-0.053	-0.07	-0.094	-0.05	-0.098	-0.36
Quarter 3	-0.141	-0.09	-0.105	-0.06	-0.083	-0.02	-0.048	-0.05
Quarter 4	0.093	0.06	0.069	0.58	0.058	0.05	-0.024	-1.05

Table B.8: CAPM market model and Fama and French five-factor plus momentum model abnormal returns based on straddled event days with an estimation window two months before and after event day T for mergers and acquisitions (M&As): Matched and random samples for controls

This table reports average abnormal returns after mergers and acquisitions (M&As) based on estimates from the CAPM market model and five-factor plus momentum (denoted FF5+Mom) model. The sample period covers events from January 1980 to December 2015. Results are shown for M&A stocks (Panel A), control stocks (Panel B), and differences between M&A stocks and both matched and random control stocks (Panels C and D). The model is estimated using returns 2 months before event day T as well as 2 months after day T (i.e., $t = 0, ..., L$). Beginning with day 0, the model is fitted in the estimation period for each stock, and $\hat{AR}_{i0}$ is computed as the forecast error on day 0. The entire process is rolled forward one day at time to create a daily time series $\hat{AR}_{i0}...\hat{AR}_{iL}$ beginning with the event announcement on day 0 and ending on the last day of the five-year, post-event period denoted day L. Abnormal returns are averaged on each day T across sample stocks. The mean $\hat{AR}$s (in percent, compounded monthly) in one year as well as quarterly increments after the event day and associated cross correlation robust t-statistics († and ‡ for 5% and 1% significance level separately) are reported.

	Market Model Matched Control		Market Model Random Control		FF5+Mom Matched Control		FF5+Mom Random Control	
Post-Event Period	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t
Panel A: M&A stocks								
Year 1	-0.141	-1.13	-0.141	-1.13	-0.090	-1.18	-0.090	-1.18
Year 2	-0.022	-0.47	-0.022	-0.47	-0.012	-0.53	-0.012	-0.53
Year 3	0.000	0.00	0.000	0.00	0.056	0.39	0.056	0.39
Year 4	-0.087	-0.86	-0.087	-0.86	-0.035	-0.85	-0.035	-0.85
Year 5	0.046	0.27	0.046	0.27	-0.004	-0.76	-0.004	-0.76
Panel B: Control stocks								
Year 1	-0.070	-0.67	-0.039	-0.41	-0.045	-0.79	-0.011	-0.28
Year 2	-0.039	-0.55	-0.010	-0.09	-0.037	-0.66	0.040	0.46
Year 3	-0.039	-0.82	-0.014	-0.22	0.031	0.55	0.020	0.14
Year 4	-0.009	-0.40	-0.008	-0.08	-0.007	-0.49	0.007	0.05
Year 5	0.016	0.44	-0.044	-0.05	0.013	0.60	-0.007	-0.35
Panel C: M&A minus control stocks								
Year 1	-0.071	-0.63	-0.102	-0.91	-0.045	-0.35	-0.079	-0.84
Year 2	0.017	0.07	-0.012	-0.41	0.025	0.10	-0.053	-0.71
Year 3	0.039	0.13	0.014	0.36	0.025	0.09	0.035	0.22
Year 4	-0.078	-0.40	-0.079	-1.01	-0.027	-0.15	-0.042	-0.87
Year 5	0.030	0.05	0.090	0.30	-0.017	-0.01	0.003	0.02
Panel D: M&A minus control stocks								
Quarter 1	-0.307	-1.27	-0.340	-1.73	-0.196	-0.73	-0.214	-1.15
Quarter 2	0.075	0.60	0.049	0.15	0.072	0.60	0.004	0.10
Quarter 3	0.031	0.01	-0.047	-0.02	-0.026	-0.14	-0.062	-0.16
Quarter 4	-0.081	-0.60	-0.070	-0.45	-0.029	-0.42	-0.043	-0.35

Table B.9: Comparative analyses using traditional BHAR and CTAR methods of abnormal returns for seasoned equity offerings (SEOs) and mergers and acquisitions (M&As): Matched and random samples for controls

This table reports average abnormal returns after seasoned equity offerings (SEOs) and mergers and acquisitions (M&As) based on traditional BHAR and CTAR methods. BHAR is the buy-and-hold abnormal return defined in equation (2.7). CTAR is the calendar time abnormal return based on the intercept term in the adjusted Fama-French five-factor plus momentum model defined in equation (2.8). Results are shown for SEO stocks (Panel A), differences between SEOs stocks and both matched and random control stocks (Panel B), M&A stocks (Panel C), and differences between M&A stocks and both matched and random control stocks (Panel D). The mean monthly $\hat{AR}$s (in percent) in each post-event year as well as in quarterly increments and associated t-statistics († and ‡ for 5% and 1% significance level separately) are reported.

	BHAR Matched Control		BHAR Random Control		CTAR Matched Control		CTAR Random Control	
Post-Event Period	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t
Panel A: SEO stocks								
Year 1					0.063	0.558	0.063	0.542
Year 2					0.126	0.802	0.126	0.826
Year 3					0.442‡	2.918	0.526‡	3.514
Year 4					0.716‡	4.571	0.695‡	4.755
Year 5					0.695‡	4.193	0.801‡	4.989
Panel B: SEO minus control stocks								
Year 1	-4.061†	-2.554	-10.882‡	-7.972	-0.607‡	-4.029	-0.231	-1.634
Year 2	-5.544‡	-3.366	-11.746‡	-8.342	-0.691‡	-4.116	-0.168	-1.092
Year 3	-3.204	-1.553	-7.142‡	-4.717	-0.503‡	-2.822	0.168	1.053
Year 4	-0.657	-0.299	-3.807†	-2.122	-0.063	-0.338	0.379†	2.278
Year 5	2.542	1.337	-4.520‡	-2.661	-0.063	-0.347	0.379†	2.058
Panel C: M&A stocks								
Year 1					0.442‡	3.603	0.421‡	3.456
Year 2					0.294†	2.056	0.294†	2.258
Year 3					0.632‡	4.335	0.738‡	5.193
Year 4					0.822‡	5.621	0.801‡	5.793
Year 5					0.759‡	4.912	0.907‡	6.386
Panel D: M&A minus control stocks								
Year 1	-1.669	-1.067	-6.422‡	-4.757	-0.231	-1.796	-0.021	-0.105
Year 2	-5.671‡	-3.102	-9.282‡	-5.857	-0.565‡	-3.521	-0.294†	-2.189
Year 3	-3.137	-1.529	-10.268‡	-3.827	-0.126	-0.714	0.126	0.762
Year 4	0.594	0.244	-35.387	-1.179	0.231	1.154	0.147	0.863
Year 5	-0.936	-0.359	-1.551	-0.813	-0.063	-0.361	0.337†	2.146

Table B.10: Robustness check using market model and Fama and French five-factor plus momentum model abnormal returns based on straddled event days with an estimation window two months before and after event day T for stock repurchases (SRs): Matched and random samples for controls

This table reports average abnormal returns after stock repurchases (SRs) based on estimates from the CAPM market model and five-factor plus momentum (denoted FF5+Mom) model. The sample period covers events from January 1980 to December 2015. Results are shown for SR stocks (Panel A), control stocks (Panel B), and differences between SRs stocks and both matched and random control stocks (Panels C and D). The model is estimated using returns 2 months before event day T as well as 2 months after day T (i.e., $T = 0, ..., L$). Beginning with day 0, the model is fitted in the estimation period for each stock, and $\hat{AR}_{i0}$ is computed as the forecast error on day 0. The entire process is rolled forward one day at time to create a daily time series $\hat{AR}_{i0}...\hat{AR}_{iL}$ beginning with the event announcement on day 0 and ending on the last day of the five-year, post-event period denoted day L. Abnormal returns are averaged on each event day T across sample stocks. The mean $\hat{AR}$s (in percent, compounded monthly) in one year as well as quarterly increments after the event day and associated cross-correlation robust t-statistics († and ‡ for 5% and 1% significance level separately) are reported.

	Market Model Matched Control		Market Model Random Control		FF5+Mom Matched Control		FF5+Mom Random Control	
Post-Event Period	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t
Panel A: SR stocks								
Year 1	0.157	0.92	0.157	0.92	0.133	1.07	0.133	1.07
Year 2	-0.028	-0.72	-0.028	-0.72	0.014	0.76	0.014	0.76
Year 3	-0.061	-0.91	-0.061	-0.91	-0.035	-1.04	-0.035	-1.04
Year 4	-0.031	-0.64	-0.031	-0.64	-0.004	-0.65	-0.004	-0.65
Year 5	0.065	0.25	0.065	0.25	0.073	0.21	0.073	0.21
Panel B: Control stocks								
Year 1	0.014	0.31	-0.017	-0.09	0.027	0.45	0.006	0.05
Year 2	-0.036	-0.65	-0.016	-0.13	0.016	0.52	0.004	0.05
Year 3	-0.042	-0.43	-0.013	-0.07	-0.015	-0.38	0.016	0.24
Year 4	-0.028	-0.91	0.006	0.07	-0.026	-1.18	0.051	0.64
Year 5	0.063	0.45	-0.031	-0.34	0.069	0.29	-0.009	-0.17
Panel C: SR minus control stocks								
Year 1	0.144	1.55	0.174	1.42	0.105	1.28	0.126	0.96
Year 2	0.008	0.05	-0.011	-0.64	-0.003	-0.01	0.009	0.58
Year 3	-0.019	-0.61	-0.048	-1.00	-0.020	-0.53	-0.051	-1.05
Year 4	-0.002	-0.03	-0.036	-0.71	0.022	0.02	-0.055	-0.94
Year 5	0.003	0.26	0.096	0.32	0.004	0.17	0.082	0.25
Panel D: SR minus control stocks								
Quarter 1	0.612†	2.42	0.837‡	3.70	0.548†	2.10	0.784‡	3.43
Quarter 2	0.039	0.51	0.029	0.02	-0.029	-0.33	-0.080	-0.63
Quarter 3	-0.069	-0.27	-0.169	-0.68	-0.076	-0.17	-0.136	-0.56
Quarter 4	-0.006	-0.33	0.003	0.06	-0.021	-0.19	-0.058	-0.19

Table B.11: Simulation analyses of RPE and traditional CTAR methods of measuring abnormal returns for seasoned equity offerings (SEOs)

This table reports rejection rates for simulation analyses of RPE and CTAR abnormal returns based on the CAPM market model. For each simulation, 500 stocks with 3 years (750 days) daily data are generated with one-year before and two years after an event date. Stocks are assigned with random event dates and corresponding market factor returns. Betas for the year before event are randomly drawn from real data. Three scenarios are introduced with different beta risk growth rates in the first year after event. Betas do not change in the second post-event year. Alphas are set at three different abnormal return levels as shown for the first half year and zero in other time periods. Residual terms are randomly drawn from actual data with the corresponding event year. Results are shown for the time period 0 to 0.5 years (or first half year) with simulated abnormal returns and risk changes (Panel A), time period 0.5 to 1.5 years with no abnormal returns but risk changes (Panel B), and time period 1.5 to 2 years with no abnormal returns and no risk changes (Panel C). Rejection rates of zero abnormal returns at the 5% level with 2,000 times simulation are reported here. All numbers are in percentage terms.

	RPE			CTAR		
	Beta Change					
Abnormal Return	0.08	0.04	0.02	0.08	0.04	0.02
Panel A: Time Period 0-0.5 Years						
1	100	100	100	82	81	82
0.5	100	100	100	83	82	83
0.1	100	100	100	83	83	84
Panel B: Time Period 0.5-1.5 Years						
1	1	1	1	88	89	89
0.5	1	0	1	89	89	89
0.1	1	1	1	88	89	89
Panel C: Time Period 1.5 -2 Years						
1	1	2	1	32	32	32
0.5	2	2	2	32	32	34
0.1	2	2	2	33	30	33

Table B.12: CAPM market model abnormal returns after seasoned equity offerings (SEOs): Matched samples for controls

This table reports average abnormal returns after seasoned equity offerings (SEOs) based on estimates from the CAPM market model. Results are shown for SEO stocks (Panel A), matched control stocks based on size and book-to-market characteristics (Panel B), and differences between SEO stocks and matched control stocks (Panels C and D). The model is estimated 1 year, 3 months, and 2 months before event day T as well as 2 months after day T, where $T = 0, ..., L$. Beginning with day 0, the model is fitted in the estimation period for each stock, and $\hat{AR}_{i0}$ is computed as the forecast error on day 0. The entire process is rolled forward one day at time to create a daily time series $\hat{AR}_{i0}...\hat{AR}_{iL}$ beginning with the event announcement on day 0 and ending on the last day of the five-year, post-event period denoted day L. Abnormal returns are averaged on each event day T across sample stocks. The mean $\hat{AR}$s (in percent, compounded monthly) in one year as well as quarterly increments after the event day and associated cross-correlation robust t-statistics († and ‡ for 5% and 1% significance level separately) are reported.

	Model Estimation Window							
	1 Year Before		3 Months Before		2 Months Before		2 Months After	
Post-Event Period	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t
Panel A: SEO stocks								
Year 1	-2.225‡	-13.22	-0.400‡	-2.63	-0.247	-1.71	0.161	1.23
Year 2	0.131	0.26	-0.118	-1.09	-0.156	-1.31	-0.010	-0.37
Year 3	0.204	0.98	-0.059	-0.53	-0.107	-0.79	-0.072	-0.01
Year 4	0.165	0.58	-0.103	-0.76	-0.179	-1.12	-0.056	-0.28
Year 5	0.103	0.23	-0.094	-0.69	-0.103	-0.73	-0.086	-0.08
Panel B: Matched control stocks								
Year 1	-0.408‡	-3.32	-0.136	-1.39	-0.157	-1.50	-0.045	-0.40
Year 2	0.064	0.14	-0.113	-1.23	-0.128	-1.31	-0.050	-0.56
Year 3	0.120	0.47	-0.099	-0.77	-0.143	-1.02	-0.041	-0.12
Year 4	-0.076	-0.59	-0.142	-0.96	-0.143	-0.97	-0.012	-0.45
Year 5	0.090	0.16	-0.057	-0.56	-0.148	-0.59	-0.047	-0.98
Panel C: SEO minus matched control stocks								
Year 1	-1.824‡	-11.47	-0.264	-1.62	-0.090	-0.45	0.207	1.89
Year 2	0.067	0.05	-0.004	-0.08	-0.029	-0.19	0.039	0.20
Year 3	0.084	0.48	0.040	0.27	0.035	0.25	-0.031	-0.17
Year 4	0.241	1.06	0.039	0.27	-0.035	-0.03	-0.044	-0.54
Year 5	0.013	0.04	-0.037	-0.17	0.045	0.26	-0.039	-0.19
Panel D: SEO minus matched control stocks								
Quarter 1	-2.328‡	-7.49	-0.827†	-2.40	-0.327	-0.76	0.860‡	3.16
Quarter 2	-2.595‡	-8.72	-0.164	-0.60	-0.007	0.00	0.133	0.51
Quarter 3	-1.961‡	-6.15	-0.307	-0.78	-0.239	-0.63	-0.104	-0.69
Quarter 4	-0.400	-1.63	0.243	0.48	0.214	0.49	-0.060	-0.47

Table B.13: Fama and French five-factor model abnormal returns after seasoned equity offerings (SEOs): Matched samples for controls

This table reports average abnormal returns after seasoned equity offerings (SEOs) based estimates from the Fama and French (1992, 1993) five-factor model. Results are shown for SEO stocks (Panel A), matched control stocks based on size and book-to-market characteristics (Panel B), and differences between SEO stocks and matched control stocks (Panels C and D). The model is estimated 1 year, 3 months, and 2 months before event day T as well as 2 months after day T, where $t = 0, ..., L$. Beginning with day 0, the model is fitted in the estimation period for each stock, and $\hat{AR}_{i0}$ is computed as the forecast error on day 0. The entire process is rolled forward one day at time to create a daily time series $\hat{AR}_{i0}...\hat{AR}_{iL}$ beginning with the event announcement on day 0 and ending on the last day of the five-year, post-event period denoted day L. Abnormal returns are averaged on each event day T across sample stocks. The mean $\hat{AR}$s (in percent, compounded monthly) in one year as well as quarterly increments after the event day and associated cross-correlation robust t-statistics(† and ‡ for 5% and 1% significance level separately) are reported.

	Model Estimation Window							
	1 Year Before		3 Months Before		2 Months Before		2 Months After	
Post-Event Period	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t
Panel A: SEO stocks								
Year 1	-1.918‡	-17.73	-0.291‡	-3.21	-0.171†	-2.04	0.264†	2.01
Year 2	-0.162	-1.48	-0.306†	-2.46	-0.363‡	-2.84	0.220	0.94
Year 3	0.138	0.85	-0.058	-1.10	-0.102	-1.45	0.062	0.82
Year 4	-0.037	-0.60	-0.096	-1.46	-0.070	-1.51	0.125	0.62
Year 5	-0.037	-0.41	-0.255	-1.83	-0.181	-1.24	0.169	1.01
Panel B: Matched control stocks								
Year 1	-0.261‡	-2.95	-0.177†	-2.09	-0.181	-1.95	0.070	0.22
Year 2	-0.083	-1.44	-0.131	-1.80	-0.152	-1.94	0.146	0.30
Year 3	0.033	0.06	-0.104	-1.15	-0.107	-1.32	0.055	0.48
Year 4	-0.196	-1.37	-0.302†	-2.20	-0.346†	-2.32	0.092	1.26
Year 5	-0.060	-0.71	-0.128	-1.13	-0.145	-0.98	0.086	0.69
Panel C: SEO minus matched control stocks								
Year 1	-1.661‡	-10.76	-0.114	-0.80	0.009	0.01	0.193	1.76
Year 2	-0.080	-0.32	-0.174	-0.61	-0.211	-0.66	0.074	0.66
Year 3	0.104	0.41	0.046	0.16	0.004	0.07	0.007	0.77
Year 4	0.159	0.63	0.206	0.37	0.277	0.36	0.032	0.32
Year 5	0.023	0.07	-0.127	-0.20	-0.036	-0.15	0.083	1.01
Panel D: SEO minus matched control stocks								
Quarter 1	-2.049‡	-6.60	-0.202	-0.49	0.182	0.67	0.906‡	2.65
Quarter 2	-2.455‡	-8.30	-0.264	-0.88	-0.246	-0.75	0.216	0.75
Quarter 3	-1.846‡	-5.86	-0.252	-0.77	-0.136	-0.57	-0.211	-0.35
Quarter 4	-0.279	-1.20	0.262	0.54	0.238	0.65	-0.134	-0.18

Table B.14: CAPM market model abnormal returns after mergers and acquisitions (M&As): Matched samples for controls

This table reports average abnormal returns after aftermergers and acquisitions (M&As) based on estimates from the CAPM market model estimates. Results are shown for M&A stocks (Panel A), matched control stocks based on size and book-to-market characteristics (Panel B), and differences between M&A stocks and matched control stocks (Panels C and D). The model is estimated 1 year, 3 months, and 2 months before event day T as well as 2 months after day T, where $t = 0, ..., T$. Beginning with day 0, the model is fitted in the estimation period for each stock, and $\hat{AR}_{i0}$ is computed as the forecast error on day 0. The entire process is rolled forward one day at time to create a daily time series $\hat{AR}_{i0}...\hat{AR}_{iL}$ beginning with the event announcement on day 0 and ending on the last day of the five-year, post-event period denoted day L. Abnormal returns are averaged on each event day T across sample stocks. The mean $\hat{AR}$s (in percent, compounded monthly) in one year as well as quarterly increments after the event day and associated cross-correlation robust t-statistics († and ‡ for 5% and 1% significance level separately) are reported.

	Model Estimation Window							
	1 Year Before		3 Months Before		2 Months Before		2 Months After	
Post-Event Period	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t
Panel A: M&A stocks								
Year 1	-0.874‡	-5.55	-0.452‡	-2.97	-0.390†	-2.56	0.050	0.42
Year 2	0.092	0.13	-0.015	-0.53	-0.050	-0.73	-0.020	-0.01
Year 3	0.191	0.70	-0.007	-0.42	-0.020	-0.49	-0.016	-0.75
Year 4	0.026	0.09	-0.184	-1.25	-0.232	-1.48	-0.019	-0.30
Year 5	0.124	0.30	0.041	0.23	0.041	0.24	0.057	0.13
Panel B: Matched control stocks								
Year 1	-0.069	-0.59	-0.064	-0.58	-0.104	-0.78	-0.114	-0.81
Year 2	0.138	0.57	-0.040	-0.46	-0.082	-0.74	-0.059	-0.30
Year 3	-0.027	-0.69	-0.187	-1.68	-0.181	-1.59	-0.042	-0.20
Year 4	-0.003	-0.29	-0.106	-0.90	-0.114	-0.88	0.010	0.18
Year 5	0.079	0.31	0.049	0.14	0.019	0.04	-0.013	-0.45
Panel C: M&A minus matched control stocks								
Year 1	-0.805‡	-5.22	-0.388†	-2.45	-0.286	-1.78	0.164	1.06
Year 2	-0.046	-0.44	0.025	0.20	0.032	0.10	0.039	0.20
Year 3	0.218	0.79	0.181	0.90	0.160	0.76	0.025	0.42
Year 4	0.029	0.40	-0.078	-0.51	-0.119	-0.64	-0.029	-0.01
Year 5	0.044	0.75	-0.008	-0.61	0.022	0.25	0.069	0.18
Panel D: M&A minus matched control stocks								
Quarter 1	-0.766‡	-2.76	-1.277‡	-4.49	-1.044‡	-3.68	0.495	1.61
Quarter 2	-0.816†	-2.43	0.117	0.79	0.147	0.84	0.028	0.84
Quarter 3	-0.867‡	-2.84	-0.129	-0.48	-0.037	-0.20	0.106	0.33
Quarter 4	-0.771‡	-2.58	-0.258	-0.75	-0.206	-0.49	0.030	0.65

Table B.15: Fama and French five-factor model abnormal returns after mergers and acquisitions (M&As): Matched samples for controls

This table reports average abnormal returns after mergers and acquisitions (M&As) based on estimates from the Fama and French (1992, 1993) five-factor model. Results are shown for M&A stocks (Panel A), matched control stocks based on size and book-to-market characteristics (Panel B), and differences between M&A stocks and matched control stocks (Panels C and D). The model is estimated 1 year, 3 months, and 2 months before event day T as well as 2 months after day T, where $t = 0, ..., L$. Beginning with day 0, the model is fitted in the estimation period for each stock, and $\hat{AR}_{i0}$ is computed as the forecast error on day 0. The entire process is rolled forward one day at time to create a daily time series $\hat{AR}_{i0}...\hat{AR}_{iL}$ beginning with the event announcement on day 0 and ending on the last day of the five-year, post-event period denoted day L. Abnormal returns are averaged on each event day T across sample stocks. The mean $\hat{AR}$s (in percent, compounded monthly) in one year as well as quarterly increments after the event day and associated cross-correlation robust t-statistics († and ‡ for 5% and 1% significance level separately) are reported.

	Model Estimation Window							
	1 Year Before		3 Months Before		2 Months Before		2 Months After	
Post-Event Period	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t
Panel A: M&A stocks								
Year 1	-0.905‡	-8.41	-0.599‡	-4.92	-0.563‡	-4.25	0.210†	2.15
Year 2	-0.130	-1.64	-0.160	-1.89	-0.145	-1.76	0.122	1.02
Year 3	0.035	0.20	-0.199	-1.90	-0.149	-1.52	0.171	0.69
Year 4	-0.079	-0.89	-0.238	-1.90	-0.327†	-2.42	0.233†	2.30
Year 5	-0.065	-0.60	-0.195	-1.57	-0.162	-1.40	0.110	0.62
Panel B: Matched control stocks								
Year 1	-0.101	-1.08	-0.112	-1.10	-0.141	-1.34	0.047	0.46
Year 2	-0.008	-0.44	-0.055	-0.97	-0.077	-1.11	0.019	0.61
Year 3	-0.169†	-1.97	-0.287‡	-2.73	-0.251†	-2.35	0.105	1.49
Year 4	-0.094	-1.05	-0.158	-1.46	-0.153	-1.41	0.182	1.39
Year 5	0.005	0.09	-0.002	-0.15	-0.063	-0.63	0.024	0.20
Panel C: M&A minus matched control stocks								
Year 1	-0.805‡	-5.26	-0.488‡	-2.60	-0.423†	-1.98	0.163	1.13
Year 2	-0.122	-1.07	-0.105	-0.73	-0.067	-0.56	0.104	0.24
Year 3	0.204	0.81	0.089	0.40	0.102	0.04	0.066	0.52
Year 4	0.015	0.19	-0.080	-0.60	-0.175	-0.92	0.051	0.63
Year 5	-0.069	-0.82	-0.193	-1.15	-0.099	-0.55	0.086	0.44
Panel D: M&A minus matched control stocks								
Quarter 1	-0.698†	-2.54	-1.188‡	-3.93	-0.934‡	-2.93	0.464	1.79
Quarter 2	-0.835†	-2.57	-0.074	-0.04	0.008	0.24	0.031	0.68
Quarter 3	-0.926‡	-2.95	-0.569	-1.08	-0.703	-1.19	0.263	0.50
Quarter 4	-0.761‡	-2.61	-0.117	-0.24	-0.060	-0.11	-0.105	-0.71

Table B.16: Robustness check using market model and Fama and French five-factor plus momentum model abnormal returns based on straddled event days with an estimation window two months before and after event day T for stock splits (SPLTs): Matched and random samples for controls

This table reports average abnormal returns after stock splits (SPLTs) based on estimates from the CAPM market model and five-factor plus momentum (denoted FF5+Mom) model. The sample period covers events from January 1980 to December 2015. Results are shown for SPLT stocks (Panel A), control stocks (Panel B), and differences between SPLTs stocks and both matched and random control stocks (Panels C and D). The model is estimated using returns 2 months before event day T as well as 2 months after day T (i.e., $T = 0, ..., L$). Beginning with day 0, the model is fitted in the estimation period for each stock, and $\hat{AR}_{i0}$ is computed as the forecast error on day 0. The entire process is rolled forward one day at time to create a daily time series $\hat{AR}_{i0}...\hat{AR}_{iL}$ beginning with the event announcement on day 0 and ending on the last day of the five-year, post-event period denoted day L. Abnormal returns are averaged on each event day T across sample stocks. The mean $\hat{AR}$s (in percent, compounded monthly) in one year as well as quarterly increments after the event day and associated cross-correlation robust t-statistics († and ‡ for 5% and 1% significance level separately) are reported.

	Market Model Matched Control		Market Model Random Control		FF5+Mom Matched Control		FF5+Mom Random Control	
Post-Event Period	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t
Panel A: SPLT stocks								
Year 1	-0.168	-1.31	-0.168	-1.31	-0.095	-1.05	-0.095	-1.05
Year 2	-0.009	-0.07	-0.009	-0.07	-0.003	-0.04	-0.003	-0.04
Year 3	-0.056	-0.43	-0.056	-0.43	0.002	0.02	0.002	0.02
Year 4	-0.020	-0.16	-0.020	-0.16	0.008	0.08	0.008	0.08
Year 5	-0.042	-0.28	-0.042	-0.28	-0.001	-0.01	-0.001	-0.01
Panel B: Control stocks								
Year 1	-0.048	-0.36	-0.036	-0.33	-0.022	-0.23	-0.012	-0.16
Year 2	-0.050	-0.38	-0.022	-0.21	-0.033	-0.32	-0.004	-0.05
Year 3	-0.064	-0.46	0.011	0.10	-0.061	-0.54	0.040	0.52
Year 4	-0.053	-0.35	-0.051	-0.45	-0.043	-0.34	-0.010	-0.12
Year 5	-0.102	-0.57	-0.015	-0.12	-0.073	-0.49	0.022	0.24
Panel C: SPLT minus control stocks								
Year 1	-0.129	-0.96	-0.118	-0.95	-0.088	-0.67	-0.145	-0.71
Year 2	0.041	0.29	0.010	0.08	0.018	0.13	0.019	0.09
Year 3	0.024	0.16	-0.047	-0.37	0.059	0.39	-0.054	-0.25
Year 4	0.019	0.11	-0.008	-0.07	0.029	0.17	0.017	0.08
Year 5	0.004	0.02	-0.024	-0.16	0.043	0.21	-0.002	-0.01
Panel D: SPLT minus control stocks								
Quarter 1	-0.575†	-2.20	-0.591†	-2.53	-0.431	-1.67	-0.575	-1.37
Quarter 2	0.045	0.18	0.079	0.36	0.056	0.22	0.057	0.15
Quarter 3	-0.008	-0.03	0.046	0.21	-0.027	-0.10	-0.058	-0.15
Quarter 4	0.051	0.20	0.006	0.03	0.075	0.29	0.007	0.02

Table B.17: CAPM market model and Fama and French five-factor plus momentum model abnormal returns based on straddled event days with an estimation window two months before and after event day T for seasoned equity offerings (SEOs) in subperiod 1980-1997: Matched and random samples for controls

This table reports average abnormal returns after seasoned equity offerings (SEOs) based on estimates from the CAPM market model and five-factor plus momentum (denoted FF5+Mom) model using data from 1980 to 1997. Results are shown for SEO stocks (Panel A), control stocks (Panel B), and differences between SEO stocks and both matched and random control stocks (Panels C and D). The model is estimated using returns 2 months before event day T as well as 2 months after day T (i.e., $T = 0, ..., L$). Beginning with day 0, the model is fitted in the estimation period for each stock, and $\hat{AR}_{i0}$ is computed as the forecast error on day 0. The entire process is rolled forward one day at time to create a daily time series $\hat{AR}_{i0}...\hat{AR}_{iL}$ beginning with the event announcement on day 0 and ending on the last day of the five-year, post-event period denoted day L. Abnormal returns are averaged on each day T across sample stocks. The mean $\hat{AR}$s (in percent, compounded monthly) in one year as well as quarterly increments after the event day and associated cross-correlation robust t-statistics († and ‡ for 5% and 1% significance level separately) are reported.

	Market Model Matched Control		Market Model Random Control		FF5+Mom Matched Control		FF5+Mom Random Control	
Post-Event Period	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t
Panel A: SEO stocks								
Year 1	0.141	0.51	0.141	0.51	0.174	1.09	0.174	1.09
Year 2	-0.064	-0.49	-0.064	-0.49	-0.055	-0.73	-0.055	-0.73
Year 3	-0.052	-0.32	-0.052	-0.32	-0.061	-0.49	-0.061	-0.49
Year 4	-0.085	-1.03	-0.085	-1.03	-0.057	-1.18	-0.057	-1.18
Year 5	-0.038	-0.36	-0.038	-0.36	0.032	0.25	0.032	0.25
Panel B: Control stocks								
Year 1	-0.076	-0.37	-0.003	-0.05	-0.031	-0.15	0.035	0.41
Year 2	-0.053	-0.31	-0.025	-0.24	0.010	0.04	-0.014	-0.18
Year 3	-0.043	-0.45	-0.001	-0.08	-0.031	-0.45	0.007	0.19
Year 4	-0.013	-0.33	-0.020	-0.18	-0.045	-0.57	0.023	0.24
Year 5	-0.060	-0.12	-0.010	-0.09	0.118	0.49	0.002	0.07
Panel C: SEO minus control stocks								
Year 1	0.217	0.82	0.144	0.65	0.205	0.78	0.139	0.72
Year 2	-0.011	-0.17	-0.039	-0.26	-0.065	-0.36	-0.041	-0.34
Year 3	-0.009	-0.11	-0.051	-0.37	-0.030	-0.04	-0.068	-0.53
Year 4	-0.072	-0.65	-0.065	-0.99	-0.012	-0.47	-0.080	-1.22
Year 5	0.023	0.48	-0.027	-0.21	-0.086	-0.41	0.030	0.14
Panel D: SEO minus control stocks								
Quarter 1	0.747†	2.03	0.518	1.86	0.792†	2.10	0.557†	2.11
Quarter 2	0.061	0.33	0.054	0.20	-0.049	-0.07	0.054	0.28
Quarter 3	-0.272	-0.83	-0.168	-0.34	-0.253	-0.75	-0.155	-0.34
Quarter 4	0.334	0.17	0.172	0.14	0.334	0.13	0.099	0.47

Table B.18: CAPM market model and Fama and French five-factor plus momentum model abnormal returns based on straddled event days with an estimation window two months before and after event day T for seasoned equity offerings (SEOs) in subperiod 1998-2015: Matched and random samples for controls

This table reports average abnormal returns after seasoned equity offerings (SEOs) based on estimates from the CAPM market model and five-factor plus momentum (denoted FF5+Mom) model using data from 1998 to 2015. Results are shown for SEO stocks (Panel A), control stocks (Panel B), and differences between SEO stocks and both matched and random control stocks (Panels C and D). The model is estimated using returns 2 months before event day T as well as 2 months after day T (i.e., $T = 0, ..., L$). Beginning with day 0, the model is fitted in the estimation period for each stock, and $\hat{AR}_{i0}$ is computed as the forecast error on day 0. The entire process is rolled forward one day at time to create a daily time series $\hat{AR}_{i0}...\hat{AR}_{iL}$ beginning with the event announcement on day 0 and ending on the last day of the five-year, post-event period denoted day L. Abnormal returns are averaged on each day T across sample stocks. The mean $\hat{AR}$s (in percent, compounded monthly) in one year as well as quarterly increments after the event day and associated cross-correlation robust t-statistics († and ‡ for 5% and 1% significance level separately) are reported.

	Market Model Matched Control		Market Model Random Control		FF5+Mom Matched Control		FF5+Mom Random Control	
Post-Event Period	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t
Panel A: SEO stocks								
Year 1	-0.156	-0.68	-0.156	-0.68	-0.035	-0.54	-0.035	-0.54
Year 2	-0.001	0.00	-0.001	0.00	-0.009	-0.80	-0.009	-0.80
Year 3	-0.017	-0.32	-0.017	-0.32	-0.005	-0.47	-0.005	-0.47
Year 4	0.006	0.31	0.006	0.31	0.034	0.31	0.034	0.31
Year 5	-0.069	-0.12	-0.069	-0.12	-0.073	-0.32	-0.073	-0.32
Panel B: Control stocks								
Year 1	-0.015	-0.83	-0.028	-0.16	0.038	0.81	0.013	0.11
Year 2	0.010	0.63	0.024	0.19	0.005	0.82	0.068	0.70
Year 3	-0.012	-0.46	0.004	0.03	-0.012	-0.51	-0.002	-0.18
Year 4	-0.023	-0.17	0.002	0.01	-0.030	-0.26	0.051	0.52
Year 5	-0.090	-0.88	0.007	0.08	0.052	1.13	0.054	0.62
Panel C: SEO minus control stocks								
Year 1	-0.141	-0.54	-0.127	-0.55	-0.072	-0.43	-0.048	-0.41
Year 2	-0.012	-0.08	-0.025	-0.76	-0.014	-0.12	-0.078	-1.14
Year 3	-0.006	-0.02	-0.021	-0.19	0.006	0.03	-0.003	-0.26
Year 4	0.028	0.11	0.004	0.41	0.064	0.01	-0.017	-0.56
Year 5	0.021	0.04	-0.076	-0.22	-0.125	-0.23	-0.127	-0.60
Panel D: SEO minus control stocks								
Quarter 1	-0.328	-0.25	-0.180	-0.64	0.044	0.41	0.281	0.42
Quarter 2	-0.032	-0.17	-0.185	-0.27	-0.153	-0.14	-0.307	-0.73
Quarter 3	0.041	0.76	-0.067	-0.22	0.149	0.84	0.043	0.38
Quarter 4	-0.244	-0.10	-0.078	-0.67	-0.327	-0.23	-0.206	-1.01

Table B.19: CAPM market model and Fama and French five-factor plus momentum model abnormal returns based on straddled event days with an estimation window two months before and after event day T for mergers and acquisitions (M&As) in subperiod 1980-1997: Matched and random samples for controls

This table reports average abnormal returns after mergers and acquisitions (M&As) based on estimates from the CAPM market model and five-factor plus momentum (denoted FF5+Mom) model using data from 1980 to 1997. Results are shown for M&A stocks (Panel A), control stocks (Panel B), and differences between M&A stocks and both matched and random control stocks (Panels C and D). The model is estimated using returns 2 months before event day T as well as 2 months after day T (i.e., $t = 0, ..., L$). Beginning with day 0, the model is fitted in the estimation period for each stock, and $\hat{AR}_{i0}$ is computed as the forecast error on day 0. The entire process is rolled forward one day at time to create a daily time series $\hat{AR}_{i0}...\hat{AR}_{iL}$ beginning with the event announcement on day 0 and ending on the last day of the five-year, post-event period denoted day L. Abnormal returns are averaged on each day T across sample stocks. The mean $\hat{AR}$s (in percent, compounded monthly) in one year as well as quarterly increments after the event day and associated cross-correlation robust t-statistics († and ‡ for 5% and 1% significance level separately) are reported.

	Market Model Matched Control		Market Model Random Control		FF5+Mom Matched Control		FF5+Mom Random Control	
Post-Event Period	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t
Panel A: M&A stocks								
Year 1	-0.113	-0.81	-0.113	-0.81	-0.057	-0.72	-0.057	-0.72
Year 2	-0.038	-0.33	-0.038	-0.33	-0.023	-0.31	-0.023	-0.31
Year 3	-0.019	-0.39	-0.019	-0.39	0.045	0.12	0.045	0.12
Year 4	-0.100	-0.76	-0.100	-0.76	-0.002	-0.01	-0.002	-0.01
Year 5	-0.006	-0.53	-0.006	-0.53	-0.085	-0.86	-0.085	-0.86
Panel B: Control stocks								
Year 1	-0.063	-0.49	-0.038	-0.27	-0.054	-0.58	-0.004	-0.05
Year 2	-0.025	-0.16	0.005	0.01	0.011	0.00	0.047	0.38
Year 3	-0.074	-0.93	-0.057	-0.30	-0.022	-0.91	-0.020	-0.11
Year 4	-0.007	-0.09	0.005	0.05	0.016	0.07	-0.007	-0.15
Year 5	-0.036	-0.54	-0.052	-0.10	-0.050	-0.65	-0.011	-0.09
Panel C: M&A minus control stocks								
Year 1	-0.050	-0.40	-0.075	-0.64	-0.003	-0.21	-0.053	-0.56
Year 2	-0.013	-0.21	-0.043	-0.34	-0.035	-0.35	-0.070	-0.48
Year 3	0.054	0.19	0.037	0.07	0.068	0.34	0.065	0.14
Year 4	-0.093	-0.33	-0.105	-0.81	-0.017	-0.21	0.005	0.50
Year 5	0.030	0.30	0.046	0.54	-0.035	-0.31	-0.074	-0.76
Panel D: M&A minus control stocks								
Quarter 1	-0.449	-1.09	-0.506	-1.73	-0.401	-0.94	-0.396	-1.36
Quarter 2	0.273	0.75	0.058	0.16	0.322	0.94	-0.020	-0.17
Quarter 3	0.079	0.08	0.335	0.86	-0.027	-0.23	0.284	0.56
Quarter 4	-0.102	-0.49	-0.184	-0.44	0.094	0.13	-0.080	-0.14

Table B.20: CAPM market model and Fama and French five-factor plus momentum model abnormal returns based on straddled event days with an estimation window two months before and after event day T for mergers and acquisitions (M&As) in subperiod 1998-2015: Matched and random samples for controls

This table reports average abnormal returns after mergers and acquisitions (M&As) based on estimates from the CAPM market model and five-factor plus momentum (denoted FF5+Mom) model using data from 1998 to 2015. Results are shown for M&A stocks (Panel A), control stocks (Panel B), and differences between M&A stocks and both matched and random control stocks (Panels C and D). The model is estimated using returns 2 months before event day T as well as 2 months after day T (i.e., $t = 0, ..., L$). Beginning with day 0, the model is fitted in the estimation period for each stock, and $\hat{AR}_{i0}$ is computed as the forecast error on day 0. The entire process is rolled forward one day at time to create a daily time series $\hat{AR}_{i0}...\hat{AR}_{iL}$ beginning with the event announcement on day 0 and ending on the last day of the five-year, post-event period denoted day L. Abnormal returns are averaged on each day T across sample stocks. The mean $\hat{AR}$s (in percent, compounded monthly) in one year as well as quarterly increments after the event day and associated cross-correlation robust t-statistics († and ‡ for 5% and 1% significance level separately) are reported.

	Market Model Matched Control		Market Model Random Control		FF5+Mom Matched Control		FF5+Mom Random Control	
Post-Event Period	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t
Panel A: M&A stocks								
Year 1	-0.160	-0.84	-0.160	-0.84	-0.112	-0.94	-0.112	-0.94
Year 2	-0.010	-0.34	-0.010	-0.34	-0.005	-0.44	-0.005	-0.44
Year 3	0.016	0.51	0.016	0.51	0.065	0.42	0.065	0.42
Year 4	-0.077	-0.46	-0.077	-0.46	-0.062	-0.54	-0.062	-0.54
Year 5	0.088	0.03	0.088	0.03	0.061	0.16	0.061	0.16
Panel B: Control stocks								
Year 1	-0.075	-0.49	-0.038	-0.32	-0.037	-0.55	-0.015	-0.31
Year 2	-0.051	-0.60	-0.022	-0.12	-0.076	-0.90	0.035	0.28
Year 3	-0.012	-0.26	0.021	0.04	0.073	0.15	0.054	0.31
Year 4	-0.011	-0.49	-0.019	-0.05	-0.027	-0.67	0.018	0.24
Year 5	0.061	0.13	-0.036	-0.07	0.066	0.08	-0.004	-0.34
Panel C: M&A minus control stocks								
Year 1	-0.085	-0.48	-0.122	-0.67	-0.075	-0.28	-0.097	-0.63
Year 2	0.041	0.09	0.012	0.26	0.071	0.19	-0.040	-0.53
Year 3	0.028	0.38	-0.005	-0.42	-0.009	-0.50	0.011	0.44
Year 4	-0.066	-0.23	-0.057	-0.60	-0.036	-0.01	-0.080	-0.77
Year 5	0.027	0.50	0.125	0.01	-0.005	-0.40	0.065	0.25
Panel D: M&A minus control stocks								
Quarter 1	-0.206	-0.72	-0.223	-0.82	-0.050	-0.11	-0.085	-0.33
Quarter 2	-0.064	-0.15	0.045	0.19	-0.104	-0.02	0.023	0.01
Quarter 3	-0.003	-0.08	-0.321	-0.69	-0.025	-0.01	-0.311	-0.67
Quarter 4	-0.065	-0.37	0.013	0.23	-0.121	-0.45	-0.017	-0.34

Table B.21: CAPM market model and Fama and French five-factor plus momentum model abnormal returns based on straddled event days with an estimation window two months before and after event day T for stock repurchases (SRs) in subperiod 1980-1997: Matched and random samples for controls

This table reports average abnormal returns after stock repurchases (SRs) based on estimates from the CAPM market model and five-factor plus momentum (denoted FF5+Mom) model using data from 1980 to 1997. Results are shown for SR stocks (Panel A), control stocks (Panel B), and differences between SRs stocks and both matched and random control stocks (Panels C and D). The model is estimated using returns 2 months before event day T as well as 2 months after day T (i.e., $T = 0, ..., L$). Beginning with day 0, the model is fitted in the estimation period for each stock, and $\hat{AR}_{i0}$ is computed as the forecast error on day 0. The entire process is rolled forward one day at time to create a daily time series $\hat{AR}_{i0}...\hat{AR}_{iL}$ beginning with the event announcement on day 0 and ending on the last day of the five-year, post-event period denoted day L. Abnormal returns are averaged on each event day T across sample stocks. The mean $\hat{AR}$s (in percent, compounded monthly) in one year as well as quarterly increments after the event day and associated cross-correlation robust t-statistics († and ‡ for 5% and 1% significance level separately) are reported.

	Market Model Matched Control		Market Model Random Control		FF5+Mom Matched Control		FF5+Mom Random Control	
Post-Event Period	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t
Panel A: SR stocks								
Year 1	0.102	0.65	0.102	0.65	0.133	0.66	0.080	0.66
Year 2	-0.038	-0.43	-0.038	-0.43	0.014	0.27	0.014	0.27
Year 3	-0.125	-1.32	-0.125	-1.32	-0.035	-1.53	-0.107	-1.53
Year 4	-0.042	-0.61	-0.042	-0.61	-0.004	-0.84	-0.034	-0.84
Year 5	0.053	0.13	0.053	0.13	0.073	0.01	0.076	0.01
Panel B: Control stocks								
Year 1	-0.037	-0.43	0.011	0.17	-0.022	-0.49	0.019	0.28
Year 2	-0.014	-0.34	-0.032	-0.28	0.033	0.12	0.009	0.06
Year 3	-0.057	-0.41	-0.044	-0.22	-0.046	-0.41	-0.048	-0.39
Year 4	-0.018	-0.25	0.023	0.15	-0.034	-0.40	0.033	0.28
Year 5	0.041	0.20	-0.046	-0.20	0.077	0.39	-0.011	-0.02
Panel C: SR minus control stocks								
Year 1	0.139	0.95	0.091	0.69	0.154	0.76	0.061	0.43
Year 2	-0.024	-0.07	-0.006	-0.20	-0.019	-0.08	0.005	0.17
Year 3	-0.068	-1.12	-0.082	-1.25	0.011	1.08	-0.059	-1.16
Year 4	-0.024	-0.05	-0.065	-0.69	0.031	0.02	-0.067	-0.84
Year 5	0.012	0.01	0.099	0.05	-0.004	-0.10	0.087	0.03
Panel D: SR minus control stocks								
Quarter 1	0.440	1.17	0.608†	2.21	0.643	1.03	0.576†	2.04
Quarter 2	0.070	0.52	-0.088	-0.26	-0.043	-0.34	-0.209	-0.71
Quarter 3	-0.239	-0.60	-0.098	-0.58	-0.238	-0.52	-0.063	-0.44
Quarter 4	0.286	0.77	-0.056	-0.05	0.258	0.65	-0.059	-0.03

Table B.22: CAPM market model and Fama and French five-factor plus momentum model abnormal returns based on straddled event days with an estimation window two months before and after event day T for stock repurchases (SRs) in subperiod 1998-2015: Matched and random samples for controls

This table reports average abnormal returns after stock repurchases (SRs) based on estimates from the CAPM market model and five-factor plus momentum (denoted FF5+Mom) model using data from 1998 to 2015. Results are shown for SR stocks (Panel A), control stocks (Panel B), and differences between SRs stocks and both matched and random control stocks (Panels C and D). The model is estimated using returns 2 months before event day T as well as 2 months after day T (i.e., $T = 0, ..., L$). Beginning with day 0, the model is fitted in the estimation period for each stock, and $\hat{AR}_{i0}$ is computed as the forecast error on day 0. The entire process is rolled forward one day at time to create a daily time series $\hat{AR}_{i0}...\hat{AR}_{iL}$ beginning with the event announcement on day 0 and ending on the last day of the five-year, post-event period denoted day L. Abnormal returns are averaged on each event day T across sample stocks. The mean $\hat{AR}$s (in percent, compounded monthly) in one year as well as quarterly increments after the event day and associated cross-correlation robust t-statistics († and ‡ for 5% and 1% significance level separately) are reported.

	Market Model Matched Control		Market Model Random Control		FF5+Mom Matched Control		FF5+Mom Random Control	
Post-Event Period	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t
Panel A: SR stocks								
Year 1	0.200	0.70	0.200	0.70	0.173	0.83	0.173	0.83
Year 2	-0.020	-0.58	-0.020	-0.58	0.013	0.73	0.013	0.73
Year 3	-0.003	-0.15	-0.003	-0.15	0.031	0.02	0.031	0.02
Year 4	-0.019	-0.31	-0.019	-0.31	0.025	0.08	0.025	0.08
Year 5	0.078	0.01	0.078	0.01	0.070	0.09	0.070	0.09
Panel B: Control stocks								
Year 1	0.057	0.09	-0.038	-0.19	0.068	0.18	-0.004	-0.12
Year 2	-0.055	-0.55	-0.004	-0.02	0.003	0.56	-0.001	-0.01
Year 3	-0.028	-0.23	0.014	0.07	0.015	0.13	0.075	0.67
Year 4	-0.039	-1.08	-0.011	-0.05	-0.016	-1.32	0.067	0.63
Year 5	0.086	0.32	-0.012	-0.07	0.062	0.36	-0.005	-0.11
Panel C: SR minus control stocks								
Year 1	0.144	1.23	0.239	1.24	0.104	1.03	0.177	0.87
Year 2	0.035	0.15	-0.016	-0.63	0.010	0.01	0.014	0.59
Year 3	0.025	0.28	-0.017	-0.29	0.016	0.36	-0.044	-0.38
Year 4	0.020	0.01	-0.008	-0.32	0.041	0.16	-0.043	-0.50
Year 5	-0.009	-0.49	0.089	0.16	0.008	0.51	0.075	0.09
Panel D: SR minus control stocks								
Quarter 1	0.744†	2.17	1.012‡	2.97	0.662	1.86	0.941‡	2.75
Quarter 2	0.014	0.23	0.121	0.17	-0.020	-0.15	0.021	0.25
Quarter 3	0.070	0.18	-0.226	-0.41	0.037	0.26	-0.194	-0.36
Quarter 4	-0.251	-0.23	0.052	0.04	-0.259	-0.32	-0.058	-0.21

Table B.23: CAPM market model and Fama and French five-factor plus momentum model abnormal returns based on straddled event days with an estimation window two months before and after event day T for stock splits (SPLTs) in subperiod 1980-1997: Matched and random samples for controls

This table reports average abnormal returns after stock splits (SPLTs) based on estimates from the CAPM market model and five-factor plus momentum (denoted FF5+Mom) model using data from 1980 to 1997. Results are shown for SPLT stocks (Panel A), control stocks (Panel B), and differences between SPLTs stocks and both matched and random control stocks (Panels C and D). The model is estimated using returns 2 months before event day T as well as 2 months after day T (i.e., $T = 0, ..., L$). Beginning with day 0, the model is fitted in the estimation period for each stock, and $\hat{AR}_{i0}$ is computed as the forecast error on day 0. The entire process is rolled forward one day at time to create a daily time series $\hat{AR}_{i0}...\hat{AR}_{iL}$ beginning with the event announcement on day 0 and ending on the last day of the five-year, post-event period denoted day L. Abnormal returns are averaged on each event day T across sample stocks. The mean $\hat{AR}$s (in percent, compounded monthly) in one year as well as quarterly increments after the event day and associated cross-correlation robust t-statistics († and ‡ for 5% and 1% significance level separately) are reported.

	Market Model Matched Control		Market Model Random Control		FF5+Mom Matched Control		FF5+Mom Random Control	
Post-Event Period	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t
Panel A: SPLT stocks								
Year 1	-0.157	-0.01	-0.157	-1.05	-0.057	-0.54	-0.057	-0.54
Year 2	-0.012	0.00	-0.012	-0.08	-0.016	-0.16	-0.016	-0.16
Year 3	-0.048	0.00	-0.048	-0.31	0.026	0.23	0.026	0.23
Year 4	-0.042	0.00	-0.042	-0.27	-0.021	-0.17	-0.021	-0.17
Year 5	-0.061	0.00	-0.061	-0.32	-0.015	-0.10	-0.015	-0.10
Panel B: Control stocks								
Year 1	-0.047	0.00	-0.029	-0.22	-0.032	-0.29	-0.017	-0.20
Year 2	-0.040	0.00	-0.017	-0.13	-0.022	-0.17	-0.017	-0.19
Year 3	-0.042	0.00	0.015	0.13	-0.038	-0.28	0.057	0.61
Year 4	-0.058	0.00	-0.058	-0.45	-0.050	-0.32	-0.026	-0.26
Year 5	-0.047	0.00	-0.006	-0.04	-0.021	-0.11	0.032	0.29
Panel C: SPLT minus control stocks								
Year 1	-0.118	-0.01	-0.114	-0.79	-0.039	-0.25	-0.030	-0.22
Year 2	0.033	0.00	-0.010	-0.07	-0.005	-0.03	-0.018	-0.13
Year 3	0.009	0.00	-0.041	-0.27	0.058	0.32	-0.009	-0.06
Year 4	-0.029	0.00	-0.033	-0.21	-0.031	-0.15	-0.042	-0.27
Year 5	0.003	0.00	-0.028	-0.16	0.047	0.18	-0.025	-0.13
Panel D: SPLT minus control stocks								
Quarter 1	-0.496	-0.02	-0.574†	-2.09	-0.373	-1.22	-0.409	-1.54
Quarter 2	0.024	0.00	0.049	0.19	0.117	0.39	0.075	0.30
Quarter 3	-0.003	0.00	0.108	0.42	0.001	0.00	0.139	0.55
Quarter 4	0.032	0.00	-0.031	-0.12	0.124	0.40	0.083	0.32

Table B.24: CAPM market model and Fama and French five-factor plus momentum model abnormal returns based on straddled event days with an estimation window two months before and after event day T for stock splits (SPLTs) in subperiod 1998-2015: Matched and random samples for controls

This table reports average abnormal returns after stock splits (SPLTs) based on estimates from the CAPM market model and five-factor plus momentum (denoted FF5+Mom) model using data from 1998 to 2015. Results are shown for SPLT stocks (Panel A), control stocks (Panel B), and differences between SPLTs stocks and both matched and random control stocks (Panels C and D). The model is estimated using returns 2 months before event day T as well as 2 months after day T (i.e., $T = 0, ..., L$). Beginning with day 0, the model is fitted in the estimation period for each stock, and $\hat{AR}_{i0}$ is computed as the forecast error on day 0. The entire process is rolled forward one day at time to create a daily time series $\hat{AR}_{i0}...\hat{AR}_{iL}$ beginning with the event announcement on day 0 and ending on the last day of the five-year, post-event period denoted day L. Abnormal returns are averaged on each event day T across sample stocks. The mean $\hat{AR}$s (in percent, compounded monthly) in one year as well as quarterly increments after the event day and associated cross-correlation robust t-statistics († and ‡ for 5% and 1% significance level separately) are reported.

	Market Model Matched Control		Market Model Random Control		FF5+Mom Matched Control		FF5+Mom Random Control	
Post-Event Period	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t
Panel A: SPLT stocks								
Year 1	-0.125	-0.54	-0.125	-0.54	-0.171	-1.01	-0.171	-1.01
Year 2	0.052	0.22	0.052	0.22	0.024	0.14	0.024	0.14
Year 3	-0.061	-0.26	-0.061	-0.26	-0.051	-0.29	-0.051	-0.29
Year 4	0.047	0.22	0.047	0.22	0.071	0.42	0.071	0.42
Year 5	-0.015	-0.06	-0.015	-0.06	0.030	0.17	0.030	0.17
Panel B: Control stocks								
Year 1	-0.050	-0.21	-0.050	-0.28	-0.002	-0.01	-0.001	-0.01
Year 2	-0.071	-0.31	-0.032	-0.17	-0.058	-0.30	0.022	0.16
Year 3	-0.113	-0.45	0.000	0.00	-0.110	-0.55	0.001	0.01
Year 4	-0.043	-0.16	-0.036	-0.17	-0.028	-0.13	0.027	0.20
Year 5	-0.229	-0.87	-0.038	-0.18	-0.194	-0.85	-0.001	-0.01
Panel C: SPLT minus control stocks								
Year 1	-0.153	-0.60	-0.125	-0.54	-0.186	-0.76	-0.145	-0.71
Year 2	0.057	0.22	0.052	0.22	0.067	0.26	0.019	0.09
Year 3	0.056	0.20	-0.061	-0.26	0.059	0.22	-0.054	-0.25
Year 4	0.129	0.47	0.047	0.22	0.167	0.59	0.017	0.08
Year 5	0.006	0.02	-0.015	-0.06	0.034	0.11	-0.002	-0.01
Panel D: SPLT minus control stocks								
Quarter 1	-0.737	-1.50	-0.626	-1.43	-0.548	-1.15	-0.575	-1.37
Quarter 2	0.089	0.20	0.141	0.35	-0.068	-0.15	0.057	0.15
Quarter 3	-0.018	-0.04	-0.082	-0.20	-0.082	-0.17	-0.058	-0.15
Quarter 4	0.091	0.20	0.082	0.20	-0.024	-0.05	0.007	0.02

Table B.25: CAPM market model, Fama and French five-factor, and Fama and French five-factor plus momentum model abnormal returns using Dimson aggregated coefficients with three leads and lags after seasoned equity offerings (SEOs)

This table reports average abnormal returns after seasoned equity offerings (SEOs) based on estimates from the CAPM market model, Fama and French five-factor and five-factor plus momentum (denoted FF5+Mom) model using data from 1980 to 2015. Results are shown for SEOs stocks (Panel A), control stocks (Panel B), and differences between SEOs stocks and matched control stocks (Panels C and D). The model is estimated using returns 2 months before event day T. Beginning with day 0, the model is fitted in the estimation period for each stock using Dimson aggregated coefficients with three leads and lags, and $\hat{AR}_{i0}$ is computed as the forecast error on day 0. The entire process is rolled forward one day at time to create a daily time series $\hat{AR}_{i0}...\hat{AR}_{iL}$ beginning with the event announcement on day 0 and ending on the last day of the five-year, post-event period denoted day L. Abnormal returns are averaged on each event day T across sample stocks. The mean $\hat{AR}$s (in percent) in one year as well as quarterly increments after the event day and associated t-statistics († and ‡ for 5% and 1% significance level separately) are reported.

	Market Model		FF5		FF5+Mom	
	2 Months Before		2 Months Before		2 Months Before	
Post-Event Period	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t	$\hat{AR}(\%)$	t
Panel A: SR stocks						
Year 1	-0.149	-1.29	-0.152	-1.32	-0.147	-1.26
Year 2	-0.050	-0.43	-0.109	-0.92	-0.084	-0.71
Year 3	-0.016	-0.12	-0.069	-0.55	-0.051	-0.40
Year 4	-0.071	-0.50	-0.115	-0.81	-0.100	-0.71
Year 5	-0.031	-0.20	-0.019	-0.12	-0.046	-0.29
Panel B: Control stocks						
Year 1	-0.101	-0.85	-0.142	-1.20	-0.125	-1.05
Year 2	-0.049	-0.38	-0.082	-0.64	-0.069	-0.54
Year 3	-0.068	-0.52	-0.085	-0.64	-0.052	-0.39
Year 4	-0.080	-0.57	-0.103	-0.74	-0.102	-0.73
Year 5	0.026	0.17	0.018	0.12	0.019	0.13
Panel C: SR minus control stocks						
Year 1	-0.048	-0.29	-0.009	-0.06	-0.022	-0.13
Year 2	-0.001	-0.01	-0.027	-0.16	-0.014	-0.08
Year 3	0.053	0.29	0.016	0.08	0.001	0.01
Year 4	0.009	0.05	-0.012	-0.07	0.002	0.01
Year 5	-0.057	-0.28	-0.037	-0.18	-0.064	-0.31
Panel D: SR minus control stocks						
Quarter 1	-0.330	-1.00	-0.158	-0.47	-0.161	-0.47
Quarter 2	0.044	0.14	0.008	0.03	-0.028	-0.09
Quarter 3	-0.225	-0.70	-0.183	-0.55	-0.164	-0.50
Quarter 4	0.320	0.88	0.295	0.80	0.265	0.72

Table B.26: CAPM market model, Fama and French five-factor, and Fama and French five-factor plus momentum model abnormal returns using Dimson aggregated coefficients with three leads and lags after mergers and acquisitions (M&As)

This table reports average abnormal returns after mergers and acquisitions (M&As) based on estimates from the CAPM market model, Fama and French five-factor and five-factor plus momentum (denoted FF5+Mom) model using data from 1980 to 2015. Results are shown for M&As stocks (Panel A), control stocks (Panel B), and differences between M&As stocks and matched control stocks (Panels C and D). The model is estimated using returns 2 months before event day T. Beginning with day 0, the model is fitted in the estimation period for each stock using Dimson aggregated coefficients with three leads and lags, and $\hat{AR}_{i0}$ is computed as the forecast error on day 0. The entire process is rolled forward one day at time to create a daily time series $\hat{AR}_{i0}...\hat{AR}_{iL}$ beginning with the event announcement on day 0 and ending on the last day of the five-year, post-event period denoted day L. Abnormal returns are averaged on each event day T across sample stocks. The mean $\hat{AR}$s (in percent) in one year as well as quarterly increments after the event day and associated t-statistics († and ‡ for 5% and 1% significance level separately) are reported.

	Market Model		FF5		FF5+Mom	
	2 Months Before		2 Months Before		2 Months Before	
Post-Event Period	$\hat{AR}$(%)	t	$\hat{AR}$(%)	t	$\hat{AR}$(%)	t
Panel A: SR stocks						
Year 1	-0.335‡	-2.77	-0.365‡	-3.11	-0.349‡	-2.98
Year 2	-0.003	-0.02	-0.063	-0.53	-0.024	-0.20
Year 3	0.020	0.15	-0.023	-0.17	0.009	0.07
Year 4	-0.139	-0.96	-0.160	-1.11	-0.083	-0.57
Year 5	-0.030	-0.21	-0.089	-0.60	-0.055	-0.38
Panel B: Control stocks						
Year 1	-0.029	-0.28	-0.042	-0.41	-0.029	-0.28
Year 2	-0.039	-0.30	-0.077	-0.60	-0.072	-0.56
Year 3	-0.101	-0.74	-0.110	-0.81	-0.071	-0.52
Year 4	-0.024	-0.17	-0.053	-0.38	0.014	0.10
Year 5	-0.020	-0.15	-0.035	-0.26	0.029	0.22
Panel C: SR minus control stocks						
Year 1	-0.306†	-2.10	-0.324†	-2.24	-0.320†	-2.21
Year 2	0.037	0.22	0.014	0.08	0.048	0.29
Year 3	0.120	0.69	0.087	0.49	0.080	0.45
Year 4	-0.115	-0.59	-0.107	-0.55	-0.097	-0.50
Year 5	-0.010	-0.05	-0.054	-0.26	-0.085	-0.41
Panel D: SR minus control stocks						
Quarter 1	-1.081‡	-3.36	-1.051‡	-3.33	-1.017‡	-3.21
Quarter 2	0.127	0.45	0.100	0.36	0.066	0.23
Quarter 3	-0.055	-0.18	-0.162	-0.56	-0.165	-0.57
Quarter 4	-0.213	-0.86	-0.178	-0.69	-0.161	-0.62

APPENDIX C

FIGURES FOR SECTION 2

Figure C.1: Daily cumulative abnormal returns (CARs) for seasoned equity offerings (SEOs) over a five-year, post-event period using estimation windows either before or after events

The plots report daily cumulative abnormal returns (CARs) seasoned equity offerings (SEOs). For the Tth event day, we compute the average portfolio $CAR_T = (1+CAR_{T-1})*(1+AR_T)-1$, where AR is the average portfolio abnormal return. The sample period covers events from January 1980 to December 2015. The Fama and French five-factor model plus momentum factor is estimated for prior event windows 1 year (Panel A), 6 months (Panel B), and 2 months (Panel C) before event day T as well as the lagged event window 2 months after day T (Panel D).

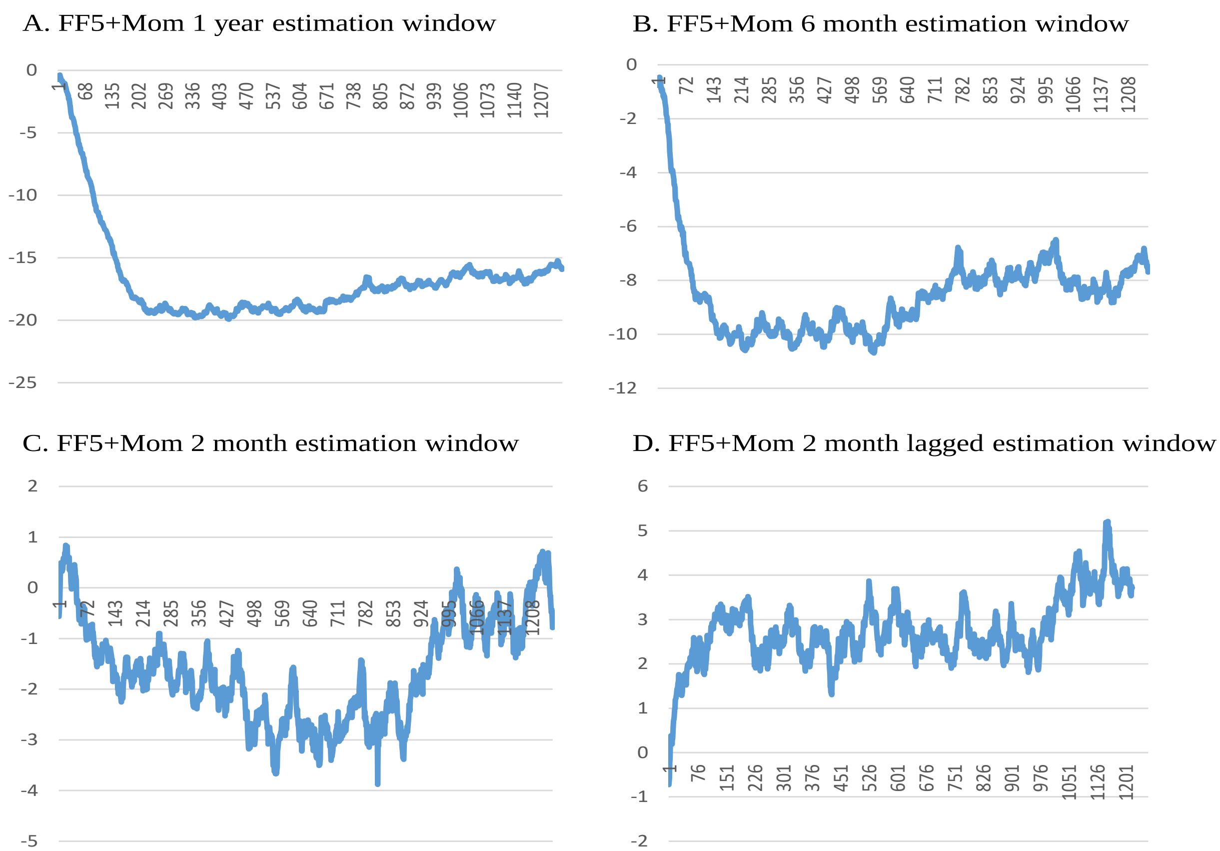


Figure C.2: Daily cumulative abnormal returns (CARs) for mergers and acquisitions (M&As) over a five-year, post-event period using estimation windows either before or after events

The plots report daily cumulative abnormal returns (CARs) mergers and acquisitions (M&As). For the Tth event day, we compute the average portfolio $CAR_T = (1 + CAR_{T-1}) * (1 + AR_T) - 1$, where AR is the average portfolio abnormal return. The sample period covers events from January 1980 to December 2015. The sample period covers events from January 1980 to December 2015. The Fama and French five-factor model plus momentum factor is estimated for prior event windows 1 year (Panel A), 6 months (Panel B), and 2 months (Panel C) before event day T as well as the lagged event window 2 months after day T (Panel D).

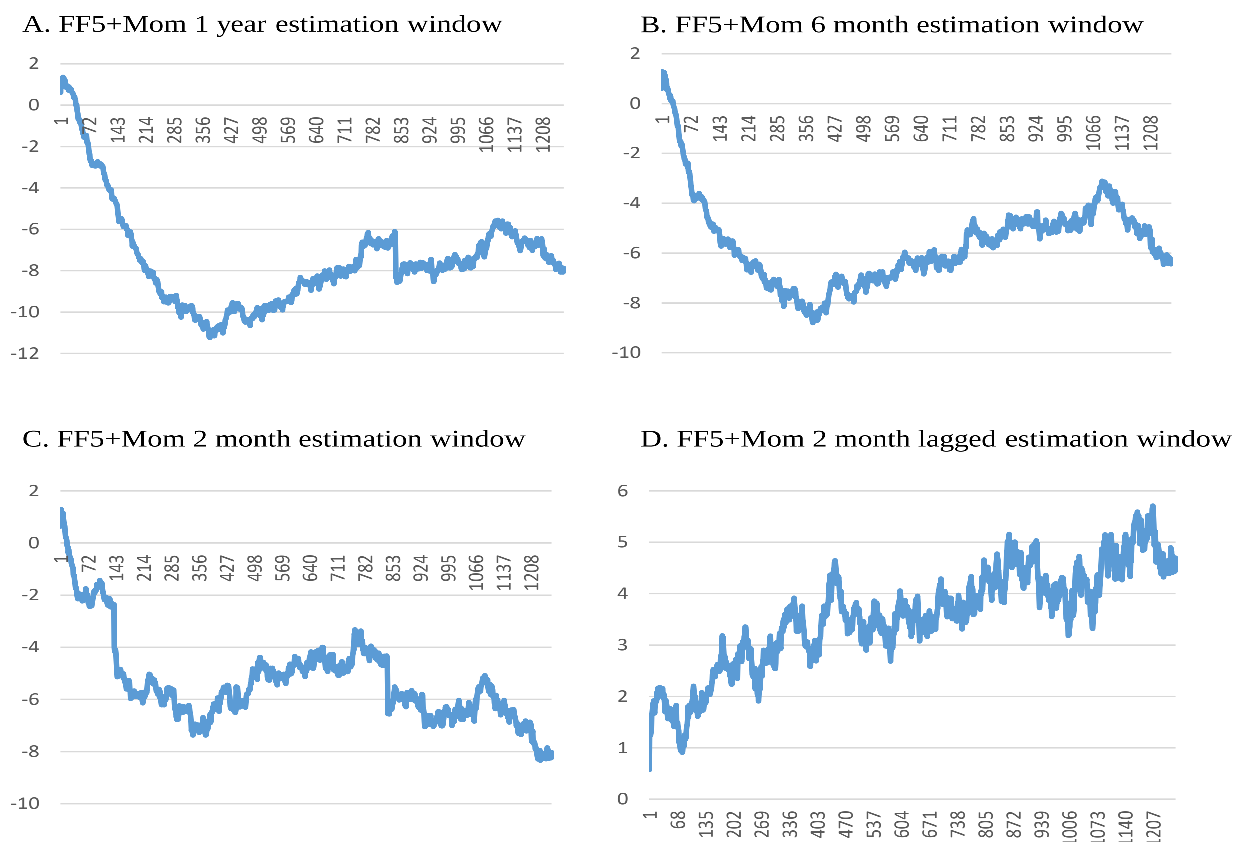
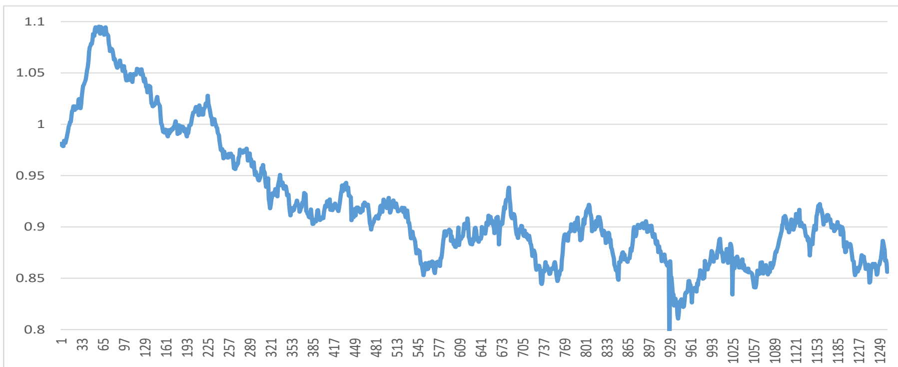


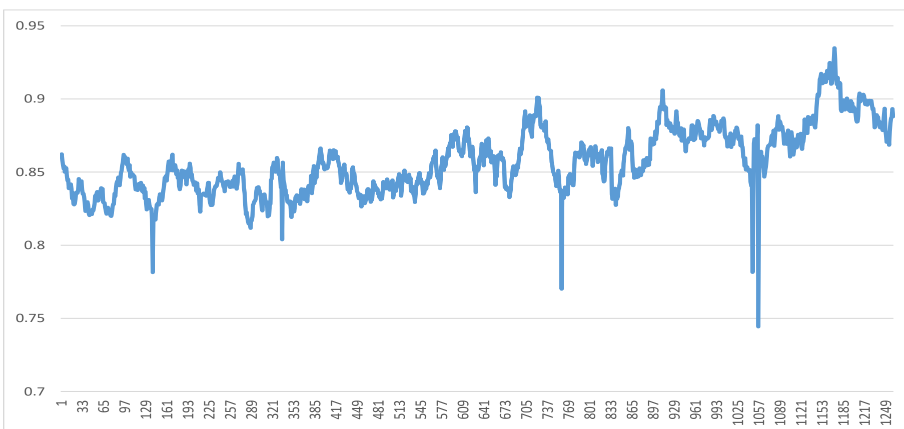
Figure C.3: Daily beta shifts for seasoned equity offerings (SEOs), mergers and acquisitions (M&As), and stock repurchases (SRs) over a five-year, post-event period using two months estimation window before event.

The plots report daily beta levels of event firms for seasoned equity offerings (SEOs), mergers and acquisitions (M&As), and stock repurchases (SRs). For the Tth event day, we estimate the average beta using two months before estimation window. The sample period covers events from January 1980 to December 2015. The CAPM market model is estimated here.

A. SEO beta shifts



B. M&A beta shifts



C. Share Repurchases beta shifts

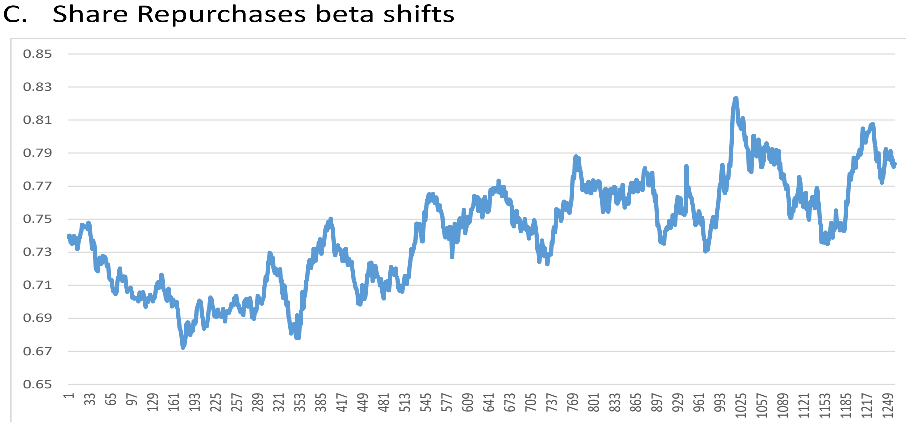
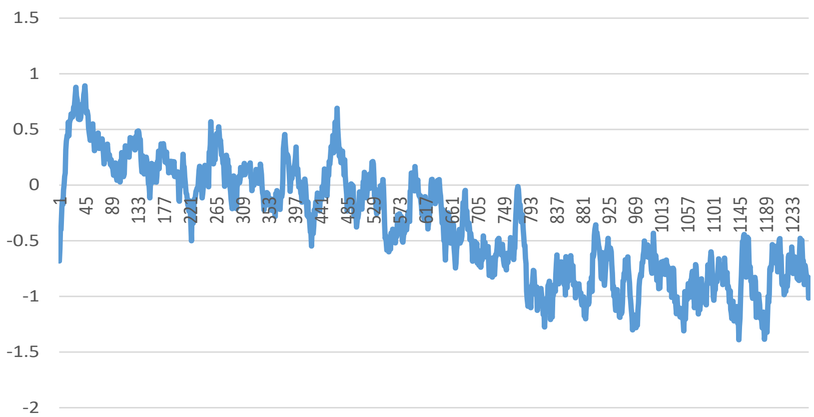


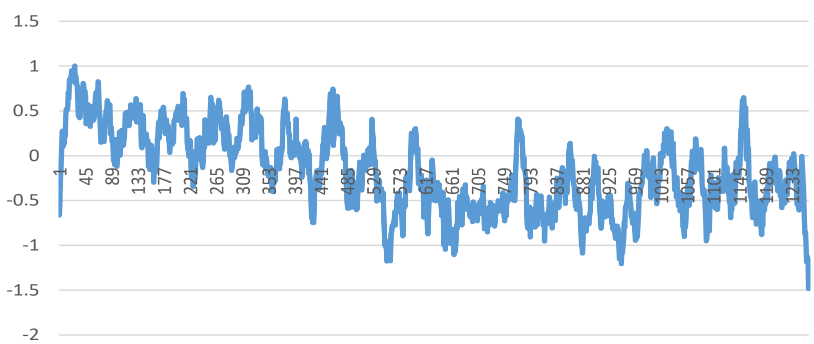
Figure C.4: Daily cumulative abnormal returns (CARs) for seasoned equity offerings (SEOs) over a five-year, post-event period using estimation both before and after event.

The plots report daily averages of cumulative abnormal returns (CARs) for seasoned equity offerings (SEOs). For the Tth event day, we compute the average portfolio $CAR_T = (1 + CAR_{T-1}) * (1 + AR_T) - 1$, where AR is the average portfolio abnormal return. The sample period covers events from January 1980 to December 2015. The Fama and French five-factor model plus momentum factor is estimated here. Panels A, B, and C contain results for SEOs, SEOs minus matched controls, and SEOs minus random samples, respectively.

A. FF5+Mom 2 month estimation window before and after event: Event stocks only



B. FF5+Mom 2 month estimation window before and after event: Event stocks minus matched control stocks



C. FF5+Mom 2 month estimation window before and after event: Event stocks minus random control stocks

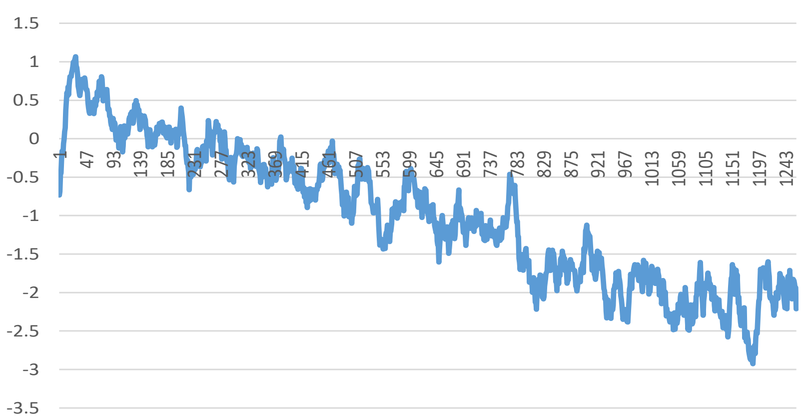
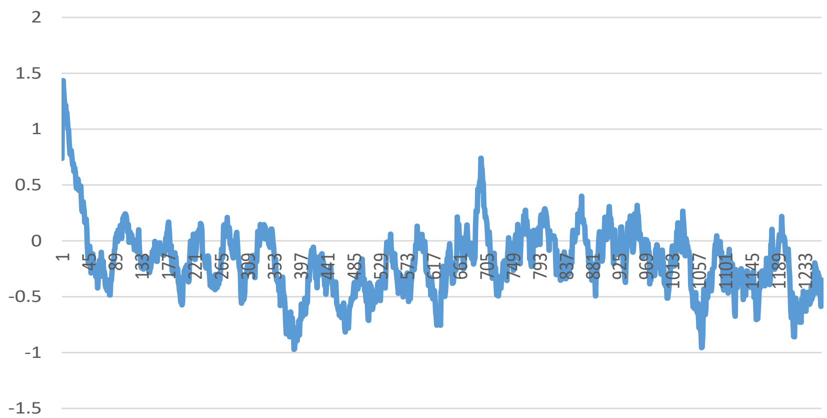


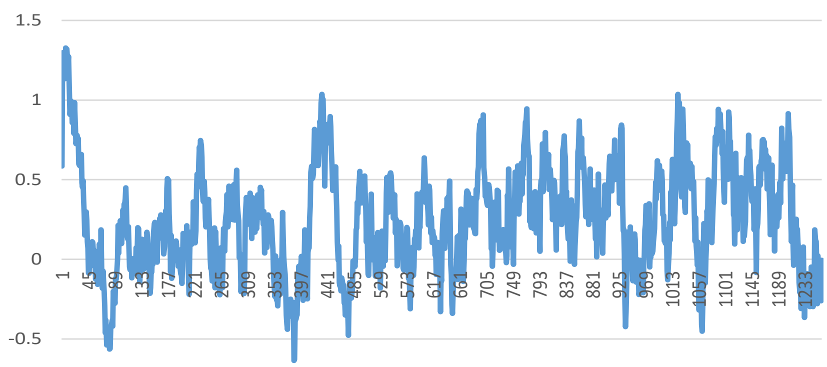
Figure C.5: Daily cumulative abnormal returns (CARs) for mergers and acquisitions (M&As) over a five-year, post-event period using estimation both before and after event.

The plots report daily averages of cumulative abnormal returns (CARs) mergers and acquisitions (M&As). For the Tth event day, we compute the average portfolio $CAR_T = (1 + CAR_{T-1}) * (1 + AR_T) - 1$, where AR is the average portfolio abnormal return. The sample period covers events from January 1980 to December 2015. The Fama and French five-factor model plus momentum factor is estimated here. Panels A, B, and C contain results for M&As, M&As minus matched controls, and M&As minus random samples, respectively.

A. FF5+Mom 2 month estimation window before and after event: Event stocks only



B. FF5+Mom 2 month estimation window before and after event: Event stocks minus matched control stocks



C. FF5+Mom 2 month estimation window before and after event: Event stocks minus random control stocks

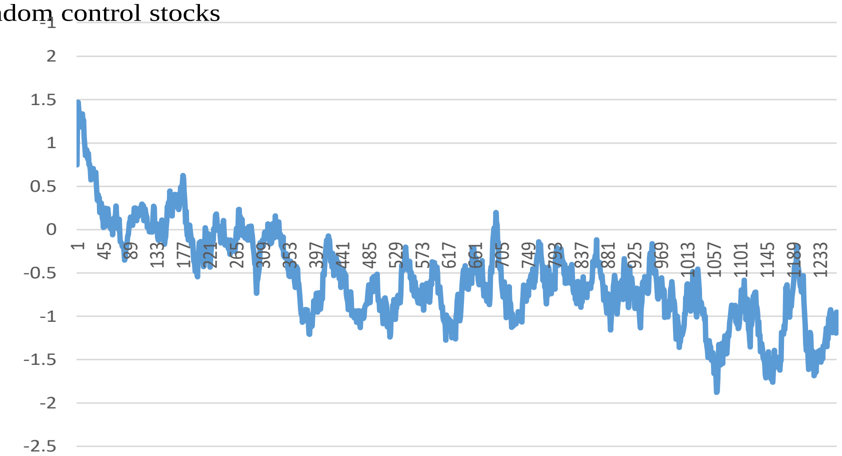
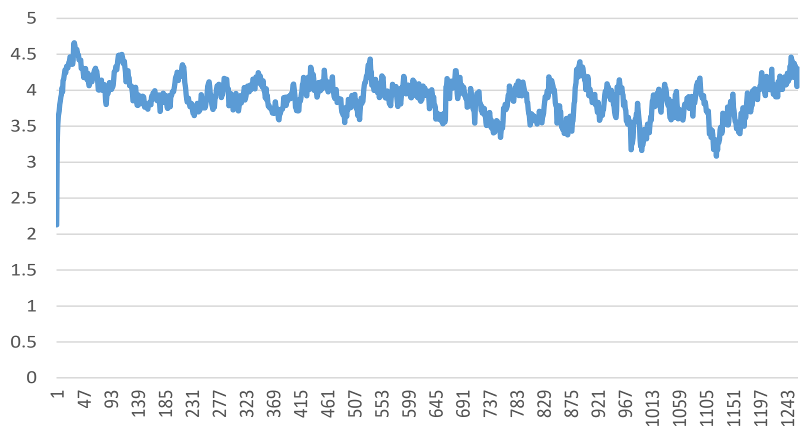


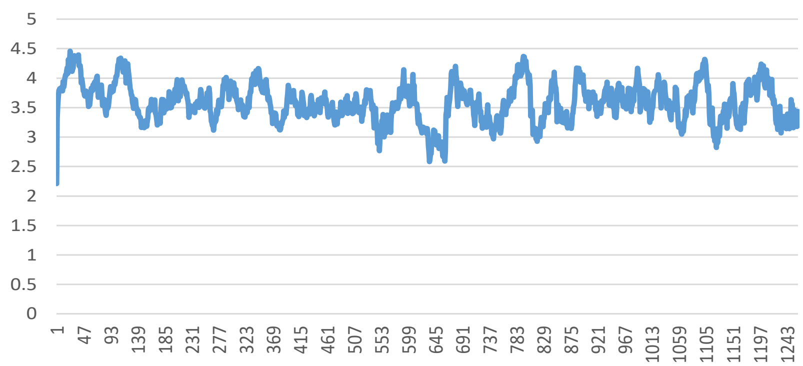
Figure C.6: Daily cumulative abnormal returns (CARs) for stock repurchases (SRs) over a five-year, post-event period using estimation windows both before and after events.

The plots report daily averages of cumulative abnormal returns (CARs) stock repurchases (SRs). The sample period covers events from January 1980 to December 2015. The Fama and French five-factor model plus momentum factor is estimated here. Panels A, B, and C contain results for SRs, SRs minus matched controls, and SRs minus random samples, respectively.

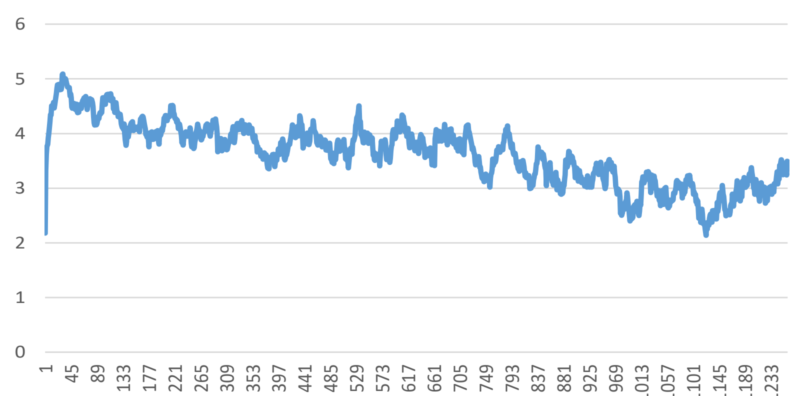
A. FF5+Mom 2 month estimation window before and after event: Event stocks only



B. FF5+Mom 2 month estimation window before and after event: Event stocks minus matched control stocks



C. FF5+Mom 2 month estimation window before and after event: Event stocks minus random control stocks



APPENDIX D

TABLES FOR SECTION 3

Table D.1: Out-of-sample monthly variances

This table reports the out-of-sample monthly variance of G portfolios, market index portfolios, and their relative changes. The sample period is from January 1968 to December 2019. Variance is calculated using excess returns. CRSP-VW and CRSP-EW represent value- and equal-weighted CRSP market index portfolios, respectively. VW and EW are the value- and equal-weighted market index portfolios, respectively, downloaded from Kenneth French's website. Four different G portfolios are shown based on the CAPM market model, Fama and French three-factor model, Carhart four-factor plus momentum model, and empirical ZCAPM model. The third and fourth columns report the variance change of the respective G portfolio compared to VW and EW portfolios (with p-values in parentheses as calculated in Ledoit and Wolf (2011)).

Model	Variance	Change-VW	Change-EW
CRSP-VW	0.0020		
CRSP-EW	0.0031		
VW	0.0020		
EW	0.0033		
G-CAPM	0.0009	-55%	-72%
		(0.000)	(0.000)
G-FF3	0.0009	-56%	-73%
		(0.000)	(0.000)
G-C4	0.0009	-53%	-71%
		(0.000)	(0.000)
G-ZCAPM	0.0010	-53%	-71%
		(0.000)	(0.000)

Table D.2: Out-of-sample return performance

This table reports out-of-sample monthly expected returns and Sharpe ratios of G portfolios, market portfolios, and their relative changes. The sample period is from January 1968 to December 2019. Expected returns are calculated as excess returns, and the Sharpe ratio is calculated as expected excess return divided by its standard deviation. CRSP-VW and CRSP-EW represent value- and equal-weighted CRSP market index portfolios, respectively. VW and EW are the value- and equal-weighted market index portfolios, respectively, downloaded from Kenneth French's website. Four different G portfolios are shown based on the CAPM market model, Fama and French three-factor model, Carhart four-factor plus momentum model, and empirical ZCAPM model. The last two columns report the Sharpe ratio change of the respective G portfolio compared to VW and EW portfolios (with p-values in parentheses as calculated in Ledoit and Wolf (2008) using 5000 times bootstrap and block size 5). Programming codes are downloaded from Michael Wolf's website.

Model	Return	Sharpe Ratio	Change - VW	Change - EW
CRSP-VW	0.51%	0.1131		
CRSP-EW	0.67%	0.1197		
VW	0.53%	0.1176		
EW	0.65%	0.1142		
G-CAPM	0.82%	0.2728	132%	139%
			(0.000)	(0.000)
G-FF3	0.80%	0.2673	127%	134%
			(0.000)	(0.000)
G-C4	0.76%	0.2452	109%	115%
			(0.000)	(0.000)
G-ZCAPM	0.82%	0.2661	126%	133%
			(0.000)	(0.000)

Table D.3: Summary statistics of individual stock weights, portfolio turnover, and performance net of transaction costs

This table reports monthly summary statistics of individual stock weights (Panel A), portfolio turnover (Panel B), and return and Sharpe ratio net of transaction costs (Panel C) for G portfolios and the value-weighted market index portfolio. The sample period is from January 1968 to December 2019. VW is the value-weighted market index portfolio downloaded from Kenneth French's website. Four different G portfolios are shown based on the CAPM market model, Fama and French three-factor model, Carhart four-factor plus momentum model, and empirical ZCAPM model. Portfolio turnover is calculated using equation (3.4) in the text. The individual stock weight is each stock's weight in the corresponding portfolio for each month during the whole sample period. We use equation (3.5) to calculate net return. Expected returns are calculated using excess net return. The Sharpe ratios are calculated as expected excess net return divided by its standard deviation.

Panel A: Individual Weight					
	VW	G-CAPM	G-FF3	G-C4	G-ZCAPM
Mean	0.02%	0.23%	0.23%	0.23%	0.23%
Min	0.00%	0.00%	0.00%	0.00%	0.00%
Max	11.36%	11.79%	10.97%	12.60%	11.23%
Std	0.11%	0.32%	0.33%	0.36%	0.29%
Panel B: Portfolio Turnover					
	VW	G-CAPM	G-FF3	G-C4	G-ZCAPM
Turnover	7.50%	31.86%	38.74%	64.59%	40.96%

Panel C: Net Transaction Costs					
	VW	G-CAPM	G-FF3	G-C4	G-ZCAPM
Return	0.49%	0.66%	0.60%	0.43%	0.62%
Sharpe	0.1092	0.2197	0.2021	0.1396	0.1996

Table D.4: G portfolios based on the largest 1000 assets

This table reports the performance of G portfolios constructed from the largest 1000 stocks by market capitalization in the CRSP database. The sample period is from January 1968 to December 2019. VW and EW are the value- and equal-weighted market index portfolios, respectively, downloaded from Kenneth French's website. Four different G portfolios are shown based on the CAPM market model, Fama and French three-factor model, Carhart four-factor plus momentum model, and empirical ZCAPM model. Expected returns and variances are calculated using excess returns and reported in the second and third columns, respectively. The Sharpe ratio is calculated as expected excess return divided by its standard deviation and reported in the fourth column. The last two columns report the variance and Sharpe ratio change of respective G portfolios compared to the value-weighted market index portfolio denoted VW downloaded from Kenneth French's website (with p-values in parentheses as calculated in Ledoit and Wolf (2008) using 5000 times bootstrap and block size 5). Programming codes are downloaded from Michael Wolf's website.

Model	Return	Variance	Sharpe Ratio	V-Diff	S-Diff
G-CAPM	0.57%	0.0010	0.1800	-50%	53%
				(0.000)	(0.045)
G-FF3	0.57%	0.0010	0.1781	-49%	52%
				(0.000)	(0.053)
G-C4	0.60%	0.0011	0.1781	-44%	52%
				(0.000)	(0.029)
G-ZCAPM	0.60%	0.0011	0.1829	-47%	56%
				(0.000)	(0.033)

Table D.5: Performance of G portfolios in different subperiods

This table reports the performance of G portfolios during different subperiods used in previously published studies. Panel A has the subperiod April 1968 to April 2005, which was studied by DeMiguel, Garlappi, Nogales, and Uppal (2009a). Panel B covers the subperiod April 1973 to April 1997, which was studied by Chan, Karceski, and Lakonishok (1999). Panel C contains results for the subperiod January 2000 to December 2013, which was studied by Maillet, Tokpavi, and Vaucher (2015). VW and EW are the value- and equal-weighted market index portfolios, respectively, downloaded from Kenneth French's website. Four different G portfolios are shown based on the CAPM market model, Fama and French three-factor model, Carhart four-factor plus momentum model, and empirical ZCAPM model. The Sharpe ratio is calculated as expected excess return divided by its standard deviation (with p-values in parentheses as calculated in Ledoit and Wolf (2008) using 5000 times bootstrap and block size 5). Programming codes are downloaded from Michael Wolf's website.

	VW	EW	G-CAPM	G-FF3	G-C4	G-ZCAPM
Panel A: 4/1968-4/2005						
Return	0.46%	0.67%	0.85%	0.80%	0.75%	0.83%
Variance	0.0022	0.0035	0.0011	0.0011	0.0011	0.0012
			(0.000)	(0.000)	(0.000)	(0.000)
Sharpe	0.0985	0.1133	0.2525	0.2425	0.2275	0.2446
			(0.001)	(0.000)	(0.002)	(0.000)
Panel B: 4/1973-4/1997						
Return	0.54%	0.70%	0.84%	0.74%	0.68%	0.80%
Variance	0.0021	0.0030	0.0012	0.0012	0.0012	0.0012
			(0.000)	(0.000)	(0.000)	(0.000)
Sharpe	0.1173	0.1273	0.2387	0.2186	0.1965	0.2280
			(0.002)	(0.005)	(0.015)	(0.002)
Panel C: 1/2000-12/2013						
Return	0.29%	0.87%	1.04%	1.06%	1.02%	1.10%
Variance	0.0022	0.0040	0.0004	0.0005	0.0006	0.0005
			(0.000)	(0.000)	(0.000)	(0.000)
Sharpe	0.0616	0.1373	0.5036	0.4875	0.4014	0.4809
			(0.000)	(0.000)	(0.000)	(0.000)

APPENDIX E

FIGURES FOR SECTION 3

Figure E.1: Difference between G portfolio and E portfolio

This figure plots the theoretical minimum variance boundary proposed by Markowitz (1952). Numbers 1 to 4 identify four different sets of individual assets. Portfolio G is the global minimum variance portfolio, and portfolio E represents an efficient portfolio with relatively higher total risk.

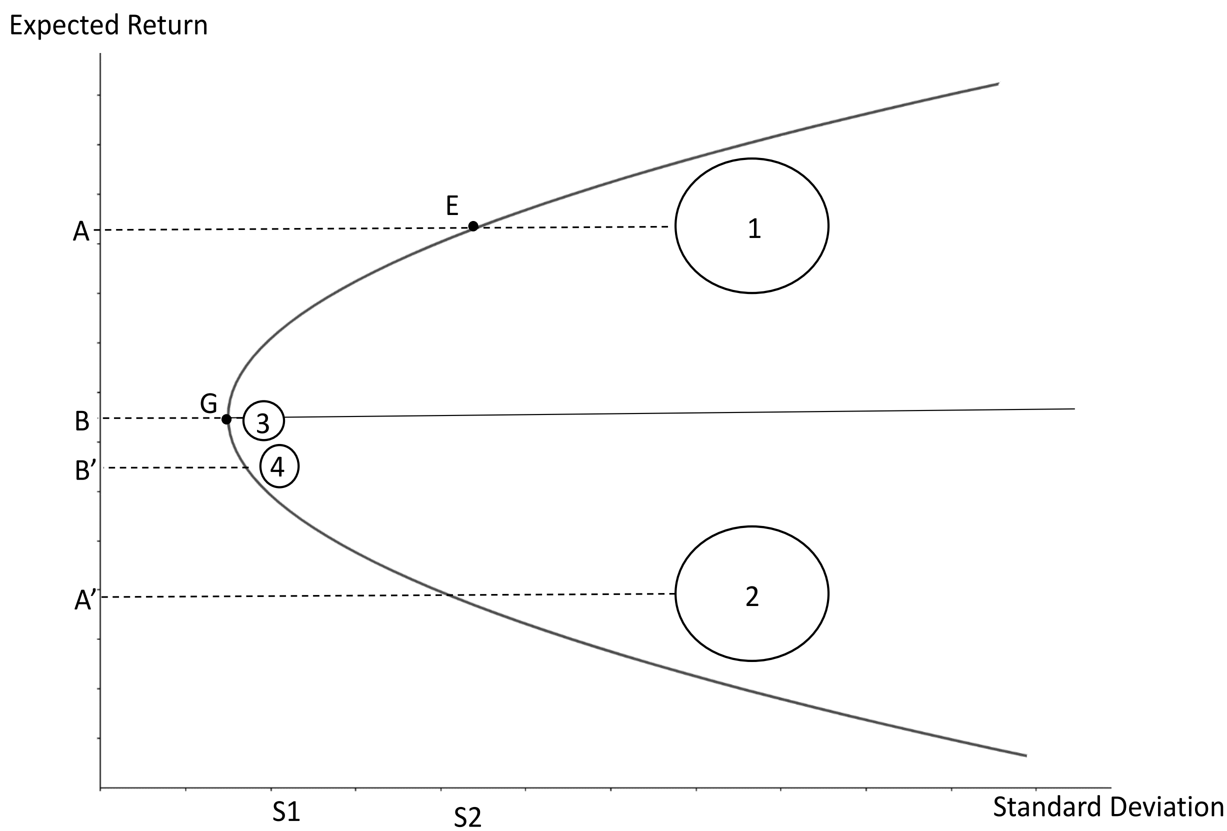


Figure E.2: Trailing 60-month rolling variance of market index portfolio and portfolio G

The plot reports the variance of excess return for two portfolios. VW (solid line) is the market index portfolio downloaded from Kenneth French's website. G-FF3 (dashed line) is the global minimum variance portfolio based on the Fama and French three-factor model. For each month T from January 1973 to December 2019, the variance of excess returns for the two portfolios in the 60 months before T is calculated and plotted.

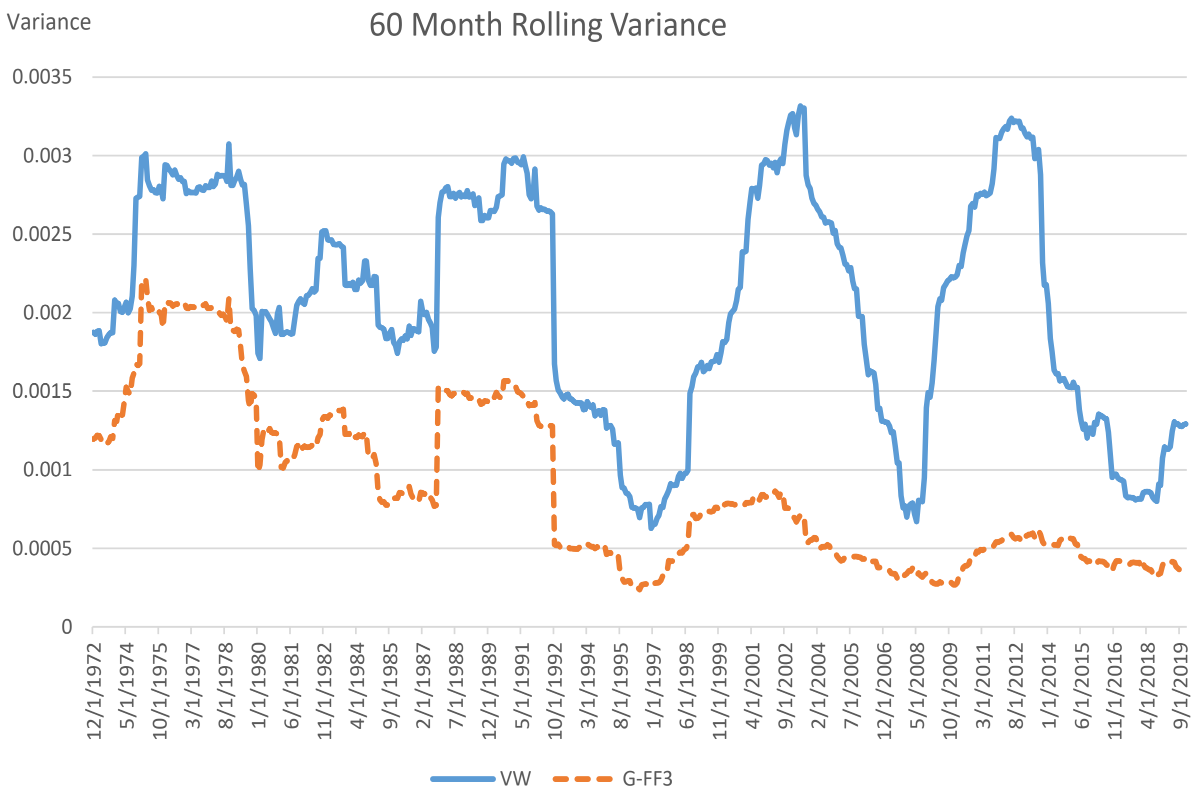


Figure E.3: Monthly return of Fama and French market index portfolio and portfolio G

The plot reports excess returns for two portfolios from January 1968 to December 2019. VW (solid line) is the market portfolio downloaded from Kenneth French's website. G-FF3 (dashed line) is the global minimum variance portfolio proposed based on the Fama and French three-factor model.