Review of Finance (2013) 17: pp. 767–808
doi:10.1093/rof/rfs012
Advance Access publication: April 25, 2012

Equity Issues and Return Volatility*

BORJA LARRAIN[1] and FELIPE VARAS[2]
[1]*Escuela de Administración and Finance UC, Pontificia Universidad Católica de Chile, and*
[2]*Graduate School of Business, Stanford University*

Abstract. We show that the repurchaser–issuer return spread is stronger among stocks with high return volatility. Rational and behavioral theories predict that this finding is the product of risk volatility and sentiment volatility, respectively. However, our results are inconsistent with these theories as they currently stand. Loadings on standard risk factors do not follow the dynamics that would explain the return predictability related to issuance decisions. If we sort on a stock's beta with respect to the aggregate sentiment index of Baker and Wurgler (2006, *J. Finance*, 61, 1645–1680), which proxies for sentiment volatility, the results are weaker—economically and statistically—than when sorting on return volatility.

JEL Classification: G12, G32

1. Introduction

It is well documented that firms issue equity when stock prices are high and shy away from equity issues or repurchase stock when prices are low. The literature refers to this empirical regularity as market timing, and in fact, this relationship has dominated much of the recent work in securities issuance (for a survey, see Ritter, 2003). In the cross-section of stocks, McLean, Pontiff, and Watanabe (2009) and Pontiff and Woodgate (2008) find that equity issuance is a strong predictor of poor returns in the USA as well as in international markets. Fama and French (2008) argue that the issuance anomaly is one of the most pervasive cross-sectional anomalies. However, there is still considerable debate about the causes and the interpretation of these facts. Some argue that they show how rational managers exploit temporary mispricing in the market by issuing equity when stocks are overpriced (see, e.g., Loughran and Ritter, 1995; Baker and Wurgler, 2000; Jenter, 2005;

* We thank seminar participants at Harvard University and Washington University (Olin), two anonymous referees, Malcolm Baker, Sergey Chernenko, Burton Hollifield (the editor), Chris Polk, Jeff Pontiff, Andrei Shleifer, Jeremy Stein, and particularly Robin Greenwood for comments and suggestions. This work was supported by the Programa Bicentenario de Ciencia y Tecnología in the context of Concurso de Anillos de Investigación en Ciencias Sociales (SOC-04 to B.L.) and by Grupo Security through Finance UC (to B.L.). This paper circulated previously with the title "Equity Issues and Sentiment Volatility."

Frazzini and Lamont, 2008; Bali, Demirtas, and Hovakimian, 2010; Greenwood and Hanson, 2012; Jenter, Lewellen, and Warner, 2011). Others argue that the comovement of prices and issues is consistent with a fully rational model that includes, for example, real options, time variation in asymmetric information, or adjustment costs in investment (see, e.g., Korajczyk, Lucas, and McDonald, 1992; Pástor and Veronesi, 2005; Carlson, Fisher, and Giammarino, 2006, 2010; Li, Livdan, and Zhang, 2009).

In this paper, we develop sharper tests of market timing in the cross-section of stocks. We make further cuts of the issuance anomaly by conditioning on firm characteristics and market variables in order to get a better sense of what drives the anomaly. In particular, we relate the return predictability that is derived from issuance activity with the level of return volatility observed in the stock. Rational and behavioral theories can account for this link depending on whether changes in risk or changes in sentiment are thought to be the main driver of return volatility. Although return volatility appears as a key conditioning variable for understanding the issuance anomaly, we show that neither the rational theory nor the behavioral theory are full explanations for the empirical results. Overall, our results pose a challenge for both rational and behavioral models as they currently stand in the literature.

We present a simple reduced-form model to develop the link between issuance, volatility, and returns that we explore empirically. The model nests rational and behavioral explanations. In particular, rational discount rates change through time affecting the issuance decision of managers. Simultaneously, managers can tailor issuance decisions to variations in investor sentiment. A manager that is a market timer issues equity to profit from bursts of investor optimism and avoids issuing when optimism turns to pessimism, even if fundamentals stay constant. In any case, rational or behavioral, the return spread between repurchasers and issuers should be positive. Large repurchasers have high returns on average because they are more likely to suffer undervaluation from negative sentiment and/or because they are more likely to be high risk stocks. On the contrary, large issuers have low returns on average because they are more likely to suffer overvaluation from positive sentiment and/or because they are more likely to be low risk stocks.

Return volatility in the model is explained by changes in three components: future cash flows, rational discount rates, and sentiment. The excess volatility literature (for a text-book treatment, see Cochrane, 2005) finds that cash flows play a secondary role and thus that return volatility is intimately related to the 2nd and 3rd components, which together encompass variation in expected returns. According to the model, expected returns become more volatile—highly positive or highly negative—as rational discount rates or sentiment become more volatile. Therefore, among stocks with high return volatility those that repurchase are more likely to have highly positive expected returns and those that issue are more likely to have highly negative expected returns. In other words, the return spread between repurchasers and issuers should be larger among stocks with high return volatility since volatility mostly captures variation in expected returns.[1]

Empirically, we find strong support for this prediction. The spread in monthly returns between repurchasers and issuers is 0.35% among low volatility stocks, while it is 0.74% among high volatility stocks. This increase in repurchaser–issuer spread of around 0.40% is highly significant. The larger spread comes from both ends, that is, from repurchasers obtaining higher average returns and from issuers obtaining lower average returns as return volatility increases.[2] In Fama–Macbeth style return regressions, we also find that being an issuer is associated with a marginal negative effect that is larger among high volatility stocks. The difference between high and low volatility stocks in the marginal effect of being an issuer is about half the size of the coefficient in the high volatility sample.

The rational explanation for this finding is that changes in risk (i.e., changes in rational discount rates) constitute the main source of return volatility and therefore for the connection between volatility, returns, and issuance decisions. Volatile issuers should experience a particularly large reduction in risk, while volatile repurchasers should experience a particularly large increase in risk. On the other hand, the behavioral explanation is that changes in sentiment constitute the main source of return volatility. Stocks with more volatile sentiment experience higher or lower future returns as more pronounced undervaluation or overvaluation is subsequently corrected. In the behavioral theory, precisely those stocks that experience the strongest undervaluation are more likely to repurchase equity, and the opposite goes for overvalued stocks.

We approach these theories directly in our empirical work. First, we examine the rational theory. At the heart of this theory is the fact that repurchasing stocks become more risky and issuing stocks less risky (see, e.g., Pástor and Veronesi, 2005; Carlson, Fisher, and Giammarino, 2006; Li, Livdan, and Zhang, 2009). For example, Carlson, Fisher, and Giammarino (2010) find in a sample of seasoned equity offerings (SEOs) that the market betas of issuers fall slowly after issuance for a period of up to 3 years. We follow a similar methodology, computing changes in market betas for issuers and repurchasers but also studying changes in the loadings of other standard risk factors in the asset pricing literature, namely HML and SMB of Fama and French. We find that volatile issuers and repurchasers alike see a decrease in their market betas and SMB betas and an increase in HML betas in the

[1] While we study issuer–repurchaser return spreads, Greenwood and Hanson (2012) study issuer–repurchaser spreads in characteristics (e.g., spreads in market-to-book ratios) and how those spreads predict returns associated with the same characteristics (e.g., HML).

[2] The evidence regarding the positive returns of repurchasers is consistent with the results of Peyer and Vermaelen (2009), although they do not explore the effect of return volatility.

years after the issuance decision. Since the dynamics of risk loadings are similar for both issuers and repurchasers, they cannot account for the return spread generated between them. Besides the direction of the effects, the average changes in factor loadings imply only small changes in expected returns (e.g., ten basis points or less). Interestingly, less volatile issuers and repurchasers experience increases in market betas and SMB betas and decreases in HML betas, which is exactly the opposite to what happens among more volatile stocks. This suggests that the dynamics of risk loadings have more to do with the volatility sorting than with issuance decisions.

Next, we turn to the behavioral theory. In this case, return volatility is associated with larger spreads between repurchasers and issuers because volatile sentiment produces strong cases of undervaluation and overvaluation. They key is that stocks that have more volatile sentiment are more likely to be opportunistic repurchasers or issuers. We take as proxy for sentiment volatility the beta of a stock with respect to the aggregate sentiment index of Baker and Wurgler (2006). Sentiment betas are positively correlated with return volatility, although the correlation is far from perfect. The spread in monthly returns between repurchasers and issuers is 0.01% among low sentiment beta stocks, while it is 0.23% among high sentiment beta stocks. Although the direction of the effect is the same as with return volatility, the magnitude of the spread is about half the one in volatility sorts and there is no statistical significance.

Overall, neither the rational explanation nor the behavioral explanation, as they currently stand, seems to give a full account for our empirical findings. This does not mean, however, that these theories are beyond repair. For instance, we are not able to find patterns in risk loadings that match the return dynamics derived from issuance, but we have studied the most commonly used risk factors in the literature. It can always be the case that we are misspecifying the expected return model by ignoring a relevant risk factor. In other words, our tests are subject to the joint hypothesis problem: we test for rationality together with a particular model for risk-adjusted returns. In terms of the behavioral theory, the results show that the volatility coming from the response to aggregate sentiment is not sufficient to explain the spread between repurchasers and issuers. However, sentiment can also be idiosyncratic, which would feed into return volatility and not into the sensitivity to aggregate sentiment. Unfortunately, idiosyncratic sentiment is harder to identify and to test for. As noted by Carlson, Fisher, and Giammarino (2010), considering the differences between aggregate and idiosyncratic sentiment may deliver testable predictions, for instance, in terms of the dynamics of market betas. The beta dynamics that we find empirically also speak against aggregate sentiment, although this only gives indirect support for the existence of idiosyncratic sentiment.

The rest of the paper is organized as follows. Section 2 develops our empirical predictions regarding the issuance–volatility–returns nexus. Section 3 presents the empirical evidence. Section 4 concludes. The Appendix to the main text contains details on the model and data description. An extensive Online Appendix contains numerous robustness checks.

2. Hypotheses Development

2.1 A SIMPLE MODEL OF ISSUANCE, RETURNS, AND VOLATILITY

In this section, we develop a simple, partial equilibrium model about equity issues, returns, and volatility. This is a reduced-form model with the intention to highlight the main channels at play. In particular, the model illustrates the risk-based (or rational) and the behavioral channels. Risk and investor biases take many different forms in fully fledged models. The reduced-form model allows us to illustrate the common predictions of these different families of models, which we then carry on to the empirical section.

There are three dates $t = 0,1,2$, and we focus on a particular stock. The interest rate is set equal to zero for simplicity. The stock represents a project with a linear technology that, for each unit of investment, yields a normally distributed payoff V at $t = 2$. The project manager has risk neutral preferences over final wealth. In addition, there is a continuum of investors with constant absolute risk aversion (CARA) preferences over final wealth, $U(W) = -e^{\gamma W}$. The coefficient γ represents the stochastic risk aversion of investors, which takes values from a distribution with support $(0, +\infty)$ and finite variance Var(γ).[3] This distribution is independent of other distributions in the model. The risk aversion of investors is common knowledge once it is revealed at $t = 1$.

At $t = 0$, there are Q_0 outstanding shares of the firm. At this time, the manager and investors share a common prior about V, given by $N(0, 1/\rho_V)$. At $t = 1$, the manager can make further investments in the project or reduce its scale (repurchase). The manager has no initial wealth and no access to debt; therefore, the only way to finance more investment is to sell equity. Before any decision is taken, both the manager and investors observe a public signal F with normal distribution $N(V, 1/\rho_F)$. On average, the signal reveals the true final cash flow of the project. However, the manager and investors interpret signals differently. We assume that investors wrongly interpret the signal as if the distribution of the signal is given by

[3] This can be interpreted as representing in reduced form the time variation in risk aversion produced by habit formation as in Campbell and Cochrane (1999) or other mechanisms.

$N(V - S, 1/\rho_F)$.[4] The random variable S, which is assumed to be independent of F, represents market sentiment.[5] Market sentiment S is taken from a normal distribution with zero mean and variance Var(S). A positive realization of sentiment implies that investors are optimistic about the final payoff since they think that the signal is taken from a distribution that on average is below the true value V. Unlike investors, the manager is assumed to have an unbiased interpretation of the signal. Beliefs conditional on the signal at $t = 1$ are given by $V|F \sim N(E^i[V|F], 1/\rho)$, for $i \in \{I, M\}$ representing investors and the manager, and where $\rho = \rho_V + \rho_F$. From Baye's rule:

$$E^{\mathrm{I}}[V|F] = \frac{\rho_F}{\rho}(F + S), \tag{1}$$

$$E^{\mathrm{M}}[V|F] = \frac{\rho_F}{\rho}F. \tag{2}$$

As seen in these equations, an investor is optimistic about future expected payoffs if $S > 0$ and pessimistic if $S < 0$. After observing the signal, the manager can sell or repurchase Q_1 shares of the project at a price P_1. Given the unitary cost of investment, P_1 can also be understood as the market-to-book ratio of the firm. Investment in the project is contractible and observable. Once the manager has invested, he remains in charge of the project until $t = 2$, when he receives a wage $w = \alpha V$, where $0 < \alpha < \frac{1}{2}$.[6] Accordingly, the manager preferences are

$$E^{\mathrm{M}}[W_{\mathrm{M}}] = E^{\mathrm{M}}[(P_1 - 1)Q_1 + \alpha V Q_1 | F]. \tag{3}$$

The investors' final wealth, with this managerial contract is given by

$$W_{\mathrm{I}} = (1 - \alpha)VX_1 - P_1 X_1, \tag{4}$$

where X_1 is the demand for the asset at $t = 1$. After observing the signal, and for a given price P_1 and level of risk aversion, investors choose how much equity to buy. Investors solve the following problem:

$$\max_{X_1} E^{\mathrm{I}}\left[-\mathrm{e}^{\gamma W_{\mathrm{I}}} | F\right], \tag{5}$$

[4] For a similar set of assumptions regarding disagreement in the interpretation of signals, see Banerjee and Kremer (2010).

[5] It is not necessary to assume independence of cash flows (F) and sentiment (S) for our results. It only simplifies the algebra.

[6] This wage can be justified in terms of agency problems. Suppose that the payoff V can only be observed by the manager, who then reports a payoff $\widehat{V}$ to shareholders. If the manager can steal $\alpha(V - \widehat{V})$, then incentive compatibility or truth telling requires the manager's wage to be αV. Therefore, the parameter α represents the stealing technology of the manager in control.

which implies a linear demand function as is standard with CARA preferences:

$$X_1(P_1) = \rho \frac{(1-\alpha)E^{\mathrm{I}}[V|F] - P_1}{(1-\alpha)^2\gamma}. \tag{6}$$

Given the demand function in Equation (6), the manager decides how much equity to issue, that is, the scale of the project. Since the manager faces a downward sloping demand his problem is similar to the one faced by a monopolist. In a model with a perfectly elastic demand for the stock, the manager issues an infinite amount of equity if the price P_1 is above the marginal cost of investment. At $t = 1$, the manager solves the following problem:

$$\max_{Q_1} E^{\mathrm{M}}[W_{\mathrm{M}}], \tag{7}$$

subject to the market clearing condition $Q_0 + Q_1 = X_1$, which can be written as

$$P_1 = (1-\alpha)E^{\mathrm{I}}[V|F] - \frac{(1-\alpha)^2\gamma}{\rho}(Q_0 + Q_1). \tag{8}$$

It is important to note that the manager cares not only about her beliefs but also about investor beliefs because they affect the price at which she expects to sell. We assume the manager knows investors sentiment (i.e., she knows S). We obtain the equilibrium price and issuance from the 1st order condition of the manager's problem.

Proposition 1. *The equilibrium price and issuance at $t = 1$ are given by*

$$P_1 = a_0 + a_1F + a_2S - a_3\gamma, \tag{9}$$

$$Q_1 = -b_0 + \frac{1}{\gamma}(b_1F + b_2S - b_3). \tag{10}$$

where all a and b coefficients are positive constants given in the Appendix.

Proposition 1 reflects the basic hypothesis of Baker and Wurgler (2000), namely that prices and equity issues are high when investor sentiment is positive ($S > 0$). Negative sentiment ($S < 0$) leads to low prices, low issuance, and potentially to repurchases ($Q_1 < 0$).[7] High risk (γ) lowers prices as a high discount rate would do. High risk also dampens the effects of future cash flows (F) and sentiment on issuance. Firms that issue a lot in this model are those with good future cash flows, strong sentiment, or low risk. Firms that repurchase a lot are those with poor future cash flows, weak sentiment, or high risk.

We define $\bar{P}_1$ as the price that would prevail in the absence of investor sentiment and as investors approach risk neutrality ($\gamma \to 0$) or simply put, $\bar{P}_1 = a_0 + a_1 F$. The difference $\bar{P}_1 - P_1$ is what we call expected returns from $t = 1$ to $t = 2$ (for a similar definition, see Chen, Hong, and Stein, 2002). Expected returns contain two pieces in this model. First, a compensation for bearing risk that is related to γ and second, the capital gain or loss that an unbiased investor can expect as prices converge to true values in $t = 2$.

Proposition 2. *The unconditional volatilities of prices and expected returns are given by*

$$\mathrm{Var}(P_1) = a_1^2 \mathrm{Var}(F) + a_2^2 \mathrm{Var}(S) + a_3^2 \mathrm{Var}(\gamma), \tag{11}$$

$$\mathrm{Var}\left(\bar{P}_1 - P_1\right) = \mathrm{Var}(a_3 \gamma - a_2 S) = a_2^2 \mathrm{Var}(S) + a_3^2 \mathrm{Var}(\gamma), \tag{12}$$

where all a coefficients are positive constants.

Prices vary in this model for three reasons: changes in future cash flows (Var(F)), changes in sentiment (Var(S)), and changes in risk or rational discount rates (Var(γ)). The excess volatility literature shows that empirically the lion's share of volatility cannot be attributed to cash flow volatility (for aggregate evidence, see Shiller, 1981 and Campbell, 1991 and for firm-level evidence, see Vuolteenaho 2002), which implies that the 2nd and 3rd terms dominate movements in prices. Proposition 2 shows that if Var(F) is small relative to the other two components of price volatility, then price volatility, and expected return volatility are closely related. This is in fact the conclusion of the excess volatility literature (see Cochrane, 2005). On the contrary, we have little to infer about the volatility of expected returns if cash flows account for most of the volatility of prices.

Proposition 2 speaks about volatility but not about the sign of expected returns. A high volatility stock can have large and positive expected returns but also large

[7] Repurchases imply a reduction of investment in this model. This is consistent with the evidence in Grullon and Michaely (2004) who find that the repurchases of US firms are best interpreted as a cheap way to increase investor payout given the lack of profitable investment opportunities.

and negative expected returns. However, from Proposition 1, we know that issuers are more likely to experience positive sentiment and low risk and repurchasers are more likely to experience negative sentiment and high risk. In other words, from the issuance policy of the firm, we can infer if expected returns are more likely to be positive or negative. Overall, Proposition 1 tells us the likely sign of expected returns and Proposition 2 tells us when we should expect those expected returns to be larger.

2.2 EMPIRICAL PREDICTIONS

Following from the propositions in the model, we take four predictions to the data.

> **Prediction 1.** *(repurchaser–issuer spread) The return spread between repurchasers and issuers should be positive.*

This prediction comes straight from Proposition 1. Large repurchasers have high returns on average because they are more likely to suffer undervaluation from negative sentiment and/or because they are more likely to be high risk stocks. On the contrary, large issuers have low returns on average because they are more likely to suffer overvaluation from positive sentiment and/or because they are more likely to be low risk stocks.

> **Prediction 2.** *(repurchaser–issuer spread and volatility) The positive return spread between repurchasers and issuers should be larger among stocks with high return volatility.*

This prediction follows from the combination of Propositions 1 and 2. From Proposition 2, we know that expected returns are more likely to be large in magnitude among stocks with high volatility. Simply put, expected returns are more likely to be highly positive or highly negative among high volatility stocks. However, Proposition 2 by itself does not tell us the sign of expected returns and that is why we need to combine it with Proposition 1. From Proposition 1, we know that repurchasers are more likely to be the stocks with positive expected returns and issuers are more likely to be the stocks with negative expected returns. Prediction 2 is, in other words, the prediction that variation in expected returns accounts for most of the variation in prices, otherwise there would be no close connection between expected returns and volatility.

> **Prediction 3.** *(risk-based prediction) The risk spread between repurchasers and issuers should be larger among stocks with high return volatility. Volatile repurchasers (issuers) should experience a particularly large increase (decrease) in risk.*

This prediction follows from identifying changes in risk (i.e., Var(γ)) as the main source of volatility in Proposition 2. Stocks that experience large changes in risk also experience more volatility as seen in Proposition 2. At the same time, these large changes in risk are more likely to detonate issuance or repurchase activity as derived from Proposition 1: large decreases in risk lead to equity issues, while large increases in risk lead to equity repurchases. Therefore, the increase in risk for repurchasers and the decrease in risk for issuers should be more pronounced among volatile stocks.

Our model does not specify the sources of change in risk or how to measure risk empirically. We describe a market where investors apply a stochastic discount factor γ, but we do not specify what risk factors are priced by investors and the origin of fluctuations in the exposure to such factors. We make this simplification in order to keep the model short and tractable. Other models in the literature have specified how the change in risk comes about and how to measure risk around issuance decisions. In reduced form, these other models give similar predictions to our Prediction 3.

There are several examples of this type of risk-based explanations.[8] First, we consider the real options model of Carlson, Fisher, and Giammarino (2006). In their model, issuance implies a decline in risk because it allows the firm to translate an investment option into a real asset. Real assets are inherently less risky than the options they replace, and therefore, issuance is correlated with a decline in risk and expected returns. We can think that this effect is particularly pronounced when stock volatility is high since option values increase with volatility. A key for this mechanism to work is that issuance has to be translated into real investment and not into other uses such as cash hoarding.

Carlson, Fisher, and Giammarino (2010) provide finer predictions of the real options model in terms of how to measure the change in risk around issuance events. The measure of risk in their model is the standard market beta of the CAPM. In a real options model with commitment to invest, beta gradually declines after issuance, which is precisely what explains the low returns post-issuance. They find support for this prediction within a sample of US SEOs. They also find that proceeds and, crucially, investment at the time of the SEO help explain the degree of decline in market betas after issuance. Extending their logic, we can conjecture that betas with respect to other standard risk factors (such as HML or SMB of Fama and French, 1993) should also experience similar dynamics around issuance.

[8] The change in risk is key to produce long-run return predictability. Other models relate issuance with changes in expected cash flows but under a constant discount rate. In these models, issuance coincides with high prices, but there is no long-run return predictability. See, for example, Dittmar and Thakor (2007), Korajczyk, Lucas, and McDonald (1992), which is a dynamic version of the model of Myers and Majluf (1984), or Pástor, Taylor, and Veronesi (2009).

In another rational model of issuance and returns, this time with adjustment costs in investment instead of real options, Li, Livdan, and Zhang (2009) also relate higher investment allowed by the issuance with lower expected returns. The intuition behind their result is that a firm's marginal q (i.e., the present value of profits generated by the marginal investment) is higher when rational discount rates are lower, therefore high investment, which follows a high q, is naturally associated with low expected returns. Investment has to accompany issuance for this explanation to have empirical bite as in the real options model.

Finally, the model in Pástor and Veronesi (2005) is a rational explanation for waves of equity issues. In their model, expected returns are time varying due to habit formation in the style of Campbell and Cochrane (1999). Low expected returns, when aggregate consumption is far from the habit level, increase the value of firms and lead to more issuance. Although this is an explanation for aggregate variables and not for the cross-section of stocks, this model also gives a rational story for the link between issuance and subsequently poor returns.

Prediction 4. *(behavioral prediction) The positive return spread between repurchasers and issuers should be larger among stocks with high sentiment volatility.*

Contrary to the 3rd prediction, this prediction follows from identifying sentiment volatility (i.e., Var(S)) as the main source of volatility in Proposition 2. For example, Baker and Wurgler (2006) argue that return volatility is a natural proxy for sentiment volatility. They show that volatile stocks comove more with an index of aggregate sentiment.[9] Volatile stocks tend to be small, young, unprofitable, non-dividend-paying, growth stocks, that is, stocks that investors typically find "hard to value." Volatile stocks are therefore more open to speculation and changes in sentiment or mistakes, and their prices are more likely to stay away from fair values. Kumar (2009) provides evidence in this respect by showing that investor mistakes (such as the disposition effect or overconfidence) are more frequent among high volatility stocks. Return volatility can also act as a limit to arbitrage: the same swings in sentiment that produce volatility keep away potential arbitrageurs who would otherwise correct investor mistakes (see DeLong *et al.*, 1990; Shleifer and Vishny, 1997; Wurgler and Zhuravskaya, 2002; Pontiff, 2006; Brav, Heaton, and Li, 2010). As emphasized by Pontiff (2006), and even if this risk is totally idiosyncratic, volatility represents the holding cost associated with an arbitrage trade and therefore it deters arbitrage.

[9] See, in particular, Figure 4 in Baker and Wurgler (2007).

3. Empirical Evidence

3.1 FIRM-LEVEL DATA

Our main data come from the intersection of Compustat and CRSP in the period 1974–2007. We exclude financial firms (SIC codes 6000–6999) and utilities (SIC codes 4900–4999) and firms with stock prices below one dollar. This gives a universe of approximately 12,000 firms with 110,000 firm-year observations. Following Baker and Wurgler (2007), return volatility is computed as the standard deviation of monthly returns from January to December for each firm.

We follow Kayhan and Titman (2007) in the construction of most variables related to capital structure (for details, see the Appendix). Our preferred definition of net equity issuance is based on balance sheet information from Compustat. An alternative definition of equity issues can be derived from the statement of cash flows, also from Compustat. A cash flow measure is potentially cleaner in terms of identifying big issuance events such as SEOs. However, as noted by Fama and French (2005), equity issues that do not involve a cash transaction but that still impact capital structure became increasingly important in the 1990s (e.g., executive compensation, equity-financed mergers). Moreover, these other channels can be particularly sensitive to market timing considerations (see, e.g., Shleifer and Vishny, 2003; Baker, Coval, and Stein, 2007 on stock-for-stock mergers and Ofek and Yermack, 2000 on executive compensation). Our results are virtually the same using both measures of equity issuance. Pontiff and Woodgate (2008) also point out that the predictability of returns derived from share issuance is not solely associated with SEOs and similar transactions.

Following Dittmar and Thakor (2007), we take as proxy for disagreement between investors and managers the cross-analyst standard deviation of earnings-per-share (EPS) forecasts from the I/B/E/S Summary History data set (unadjusted for splits). We normalize the standard deviation by the absolute value of the mean forecast following Diether, Malloy, and Scherbina (2002). We aggregate quarterly EPS forecasts in the following way. First, for each firm in each quarter, we collapse the observations of mean forecast and standard deviation to a single observation. The I/B/E/S cycle of only a few weeks implies that the same estimates are many times repeated within the same quarter providing little extra information. Then, we average each variable for each firm across the four quarters in the year to get an annual measure. We focus on quarterly forecasts because annual forecasts have a mechanic downward trend in their standard deviation as the end of the fiscal year approaches and less information remains unknown. Once we match I/B/E/S with Compustat for financial information, our sample covers approximately 6,000 firms between the years 1984 and 2007. This sample is about one-third of the size of the

Table I. Correlation matrix

Variable definitions are provided in the main text and the Appendix. All variables are winsorized at the 1% and 99% levels.

	Return volatility	Market capitalization	*M/B*	Sales	Tangibility	ROA	Leverage	Cash	Dividends	KZ	ROA Volatility	Analyst SD	*I/K*
Return volatility	1.00												
Market capitalization (log)	−0.32	1.00											
M/B	0.19	0.21	1.00										
Sales (log)	−0.42	0.74	−0.21	1.00									
Tangibility	−0.21	0.12	−0.20	0.22	1.00								
ROA	−0.36	0.28	−0.07	0.46	0.20	1.00							
Leverage	−0.10	0.06	−0.14	0.35	0.21	−0.03	1.00						
Cash balance	0.31	−0.11	0.32	−0.40	−0.37	−0.30	−0.31	1.00					
Dividends	−0.25	0.24	0.06	0.22	0.14	0.16	0.12	−0.10	1.00				
KZ index	0.08	−0.13	−0.25	0.06	0.14	−0.20	0.47	−0.29	−0.61	1.00			
ROA volatility	0.35	−0.19	0.24	−0.37	−0.15	−0.51	−0.03	0.30	−0.07	0.01	1.00		
Analyst standard deviation	0.13	−0.18	−0.07	−0.11	0.03	−0.14	0.07	0.02	−0.07	0.11	0.09	1.00	
I/K	−0.02	−0.01	−0.01	−0.02	0.64	0.14	0.04	−0.17	−0.01	0.05	−0.01	0.02	1.00

merged CRSP–Compustat sample that we use for the tests that do not require data from I/B/E/S.[10]

Table I presents correlations between firm-level characteristics at the annual frequency. We winsorize all variables at the 1% level in order to minimize the impact of outliers. As noted by Baker and Wurgler (2006), high return volatility tends to be associated with small, unprofitable, and nondividend-paying firms. The Kaplan and Zingales (KZ, 1997) index is a summary of variables that are empirically associated with financial constraints.[11] The correlation of return volatility with the KZ index is positive but relatively small (0.08). Return volatility is also positively correlated with ROA volatility (0.35).

In order to avoid confounding effects, we also compute a measure of return volatility that is orthogonal to other firm characteristics. In other words, this measure is uncorrelated with the degree of cash-flow volatility, financial constraints, and so on. We compute this measure by running a panel regression of volatility on the firm characteristics reported in Table I (excluding the cross-analyst standard deviation because of its narrow coverage) and then computing the residual from that regression. The R-squared of the regression is approximately 25%, which shows that substantial variation in volatility across firms and time is left unexplained by observable firm characteristics. The residual volatility still has a strong correlation with raw volatility (0.86), despite being uncorrelated—by construction—with the other firm characteristics. Given this high correlation, all of our portfolio sorts and regressions using raw volatility are almost identical with residual volatility. We present some of them using residual volatility, but for the most part, we focus on raw volatility since this is the most straightforward measure and it allows direct comparison with other papers.

The Online Appendix provides extensive robustness checks for the key results in this paper. In this Appendix, we study different measures of equity issuance and return volatility, alternative portfolio sorts, returns for longer holding periods (quarterly and annual), and alternative regression specifications not considered in the main text.

[10] Around 2% of the firm-year observations have a standard deviation of zero because most likely these firms are covered by few analysts. In order to have a standard deviation of analysts' forecasts, the stock has to be covered by at least two analysts.

[11] We follow Baker, Stein, and Wurgler (2003) in the construction of this index. For example, we exclude the market-to-book ratio from it.

Table II. Average and cross-sectional standard deviations of equity issues for portfolios sorted according to issuance activity and return volatility

We form six portfolios of issuance activity: large and small repurchases (including zero issuance) plus four quartiles within observations with positive net equity issues. We sort independently into five size (market capitalization in June of year *t*) quintiles and then within each size quintile into high and low return volatility. Finally, we pull together observations for high and low return volatility across size quintiles. Within each one of the twelve resulting portfolios, we compute equally weighted averages (or cross-sectional standard deviations) each year. This table shows the average of these measures across years. All numbers are multiplied by 100.

	Return volatility			
	Low	High	Low	High
	Average net issues		Standard deviation of net issues	
Large repurchases	−5.27	−5.67	4.66	5.29
Small repurchases	−0.48	−0.42	0.49	0.46
Small issues	0.35	0.34	0.30	0.30
Q2 issues	1.62	1.76	0.93	1.03
Q3 issues	6.34	7.85	5.28	6.58
Large issues	25.46	40.22	23.61	30.92

3.2 PREDICTIONS 1 AND 2: EQUITY ISSUES, FUTURE RETURNS, AND VOLATILITY

2.2.a. Portfolio sorts

We first explore portfolio returns. The returns from July of year t to June of year $t+1$ are sorted into portfolios according to the firm's issuance activity in year $t-1$. We create six portfolios of issuance activity following a similar methodology as Fama and French (2008). The 1st two portfolios have large repurchases and small repurchases (including zero issuance). The other four portfolios contain from small to large issues (quartiles computed within observations of positive issuance). As can be seen in Table II, the extreme portfolios have much higher cross-sectional standard deviation of issuance than the other portfolios.[12]

We sort stocks independently into portfolios of high and low return volatility, also measured in year $t-1$. The sorting procedure for these two groups is similar to the one in Chen, Hong, and Stein (2002), so groups are not dominated by small or large firms. First, every June we split the sample into five quintiles of market capitalization.[13] Then, within each size quintile, we form a high and low group using

[12] The summary statistics we report in Table II are very similar to those in Table III of Fama and French (2008).

[13] Market capitalization is defined as the log of market cap (price times shares outstanding, both from CRSP) in June of year *t*.

Table III. Average returns and t-statistics for portfolios sorted according to issuance activity and return volatility

We form six portfolios of issuance activity: large and small repurchases (including zero issuance) plus four quartiles within observations with positive net equity issues. We sort independently into five size (market capitalization in June of year t) quintiles and then within each size quintile into high and low return volatility. Finally, we pull together observations for high and low return volatility across size quintiles. Within each one of the twelve resulting portfolios, we compute equal-weighted and value-weighted returns each month. This table shows the average return across months. Size- and B/M-adjusted returns subtract from the raw return of each firm the return of a benchmark portfolio based on independent sorts into size and book-to-market NYSE quintiles (for details, see Fama and French 2008). Average returns are multiplied by 100. We use two measures of volatility: raw return volatility and residual volatility, which corresponds to the residual of a regression of return volatility on the other firm characteristics considered in Table I.

	Residual Return Volatility				Residual Return Volatility			
	Low	High	Low	High	Low	High	Low	High
	Average returns		t-statistics		Average returns		t-statistics	
	(A) Equal-weighted raw returns				(C) Size- and B/M-Adjusted equal-weighted returns			
Large repurchases	1.52	1.83	6.90	5.57	0.05	0.43	0.59	3.78
Small repurchases	1.64	1.99	7.42	6.20	0.17	0.64	2.09	5.74
Small issues	1.54	1.75	6.82	5.42	0.15	0.47	2.07	4.76
Q2 issues	1.42	1.65	6.16	4.67	0.07	0.45	0.93	3.68
Q3 issues	1.32	1.45	5.45	3.90	0.04	0.29	0.55	2.31
Large issues	1.17	1.09	3.77	2.52	0.11	0.06	0.98	0.32
Large repurchases − large issues (LRMLI)	**0.35**	**0.74**	**2.08**	**5.62**	**−0.07**	**0.38**	**−0.49**	**2.85**
High LRMLI − low LRMLI		**0.40**		**3.01**		**0.44**		**3.24**
	(B) Value-weighted raw returns				(D) Size- and B/M-adjusted value-weighted Returns			
Large repurchases	1.43	1.58	6.55	4.89	0.02	0.18	0.33	1.99
Small repurchases	1.47	1.65	6.70	5.24	0.07	0.28	1.03	3.03
Small issues	1.41	1.50	6.32	4.74	0.05	0.19	0.92	2.35
Q2 issues	1.34	1.45	5.92	4.20	0.05	0.23	0.77	2.19
Q3 issues	1.25	1.29	5.23	3.52	0.02	0.12	0.42	1.07
Large issues	1.00	0.85	3.29	1.98	−0.05	−0.16	−0.56	−1.05
Large repurchases − large issues (LRMLI)	**0.43**	**0.73**	**2.59**	**4.18**	**0.08**	**0.35**	**0.64**	**3.04**
High LRMLI − low LRMLI		**0.31**		**2.50**		**0.27**		**2.45**

Continued

Table III. Continued

	Residual Return Volatility				Residual Return Volatility			
	Low	High	Low	High	Low	High	Low	High
	Average returns		*t*-statistics		Average returns		*t*-statistics	
	(A) Equal-weighted raw returns				(C) Size- and *B*/*M*-Adjusted equal-weighted returns			
Large repurchases	1.57	1.77	6.62	5.59	0.11	0.36	1.38	3.58
Small repurchases	1.64	1.84	7.05	5.92	0.16	0.49	1.88	4.74
Small issues	1.56	1.69	6.49	5.43	0.21	0.36	2.90	3.88
Q2 issues	1.44	1.64	5.77	4.85	0.14	0.40	1.98	3.60
Q3 issues	1.34	1.44	4.79	4.01	0.10	0.28	1.55	2.31
Large issues	1.21	1.02	3.27	2.32	0.24	-0.02	1.86	-0.11
Large repurchases − large issues (LRMLI)	**0.36**	**0.74**	**1.68**	**3.66**	**-0.13**	**0.38**	**-0.84**	**2.47**
High LRMLI − low LRMLI		**0.38**		**2.92**		**0.51**		**3.85**
	(B) Value-weighted raw returns				(D) Size- and *B*/*M*-adjusted value-weighted Returns			
Large repurchases	1.44	1.58	6.14	5.14	0.03	0.19	0.40	2.32
Small repurchases	1.47	1.54	6.29	5.15	0.05	0.20	0.76	2.40
Small issues	1.41	1.48	5.92	4.90	0.08	0.14	1.32	1.91
Q2 issues	1.37	1.45	5.56	4.46	0.10	0.20	1.72	2.11
Q3 issues	1.27	1.30	4.59	3.68	0.06	0.14	0.97	1.24
Large issues	1.03	0.80	2.85	1.81	0.02	-0.22	0.21	-1.27
Large repurchases − large issues (LRMLI)	**0.41**	**0.78**	**1.91**	**3.74**	**0.01**	**0.40**	**0.04**	**2.84**
High LRMLI − low LRMLI		**0.37**		**3.01**		**0.40**		**3.60**

the median of return volatility in that quintile. Finally, we put together the firms with high return volatility from all size quintiles into a single group and identically for firms with low return volatility. With this procedure, both groups of return volatility represent a balanced sample of small and big firms. This procedure is relevant given the relatively high correlation of return volatility and size in the data.

In Table III, we report average returns for the twelve resulting portfolios (six with low volatility and six with high volatility). We present raw returns and adjusted returns as in Fama and French (2008). The adjustment is done by subtracting from the raw return the return of a benchmark portfolio for each stock based on independent sorts of market capitalization and book-to-market New York Stock Exchange (NYSE) quintiles.[14] Furthermore, we present equal-weighted and value-weighted portfolio returns. Since the results are very similar in both cases, we comment only on the equal-weighted returns.

[14] The book-to-market ratio is book equity (Compustat data item 60) over market cap in December of year $t - 1$.

We first confirm the negative effect of equity issuance on returns: portfolios of large issues have lower average returns than portfolios of large repurchases.[15] This is true irrespective of whether we look at raw returns or adjusted returns. Our 2nd prediction is that the large-repurchases-minus-large-issues (LRMLI) spread should be larger among stocks with high return volatility. In fact, the spread in raw returns is 0.74% (0.38% in adjusted returns) when return volatility is high and 0.35% (−0.07% in adjusted returns) when return volatility is low. The difference in LRMLI spreads between groups of return volatility is 0.40% in raw returns (0.44% in adjusted returns) with a *t*-statistic of 3.01 (3.24 in adjusted returns). Importantly, the larger spread does not come from the behavior of large issuers alone. Large repurchasers in the high volatility group yield higher returns than large repurchasers in the low volatility group. In the 2nd panel in Table III, we form portfolios based on the residual volatility that is orthogonal to other firm characteristics. We find very similar results as those reported above, and if anything even stronger results.

Figure 1 summarizes these results in event time around portfolio formation (for a similar methodology, see Cooper, Gulen, and Schill 2008). For visual clarity, we present average annual returns, so there is a single observation in the figure for each portfolio in each year. We express annual returns on a monthly basis, so the magnitudes are comparable to the returns reported in Table III. Figure 1A shows the returns for the more volatile repurchasers and issuers. Issuers have very high returns 2 years before portfolio formation, while repurchasers have very low returns at the same time. However, in the 1st couple of years after portfolio formation, we see a spread between repurchasers and issuers of about 0.70%, which is very similar to the one reported in Table III. In the case of the less volatile stocks in Figure 1B, the spread between repurchasers and issuers is basically zero in the 1st year after portfolio formation and about 0.30% in the 2nd year.

It is worth emphasizing that we compute issuer–repurchaser spreads among stocks of similar volatility, and therefore, our results are not contaminated by the finding of Ang *et al.* (2006) of a negative abnormal return for high volatility stocks. Their finding is across volatility groups, while ours is within volatility groups. The negative alpha affecting all volatile stocks should not distort the spread between volatile repurchasers and volatile issuers. Moreover, our Table III suggests that the negative abnormal returns of high volatility portfolios are mostly due to the negative abnormal returns of large issuers within that group. Ang *et al.* (2006) actually find a concave function for abnormal returns and volatility, with abnormal returns rising initially from low to medium volatility and only decreasing and turning negative from medium to high volatility. This can also be seen in our Table III,

[15] Again, and for comparison, see the returns of similar portfolios in Table II of Fama and French (2008). Our numbers are very close, in particular for portfolios in the extremes.

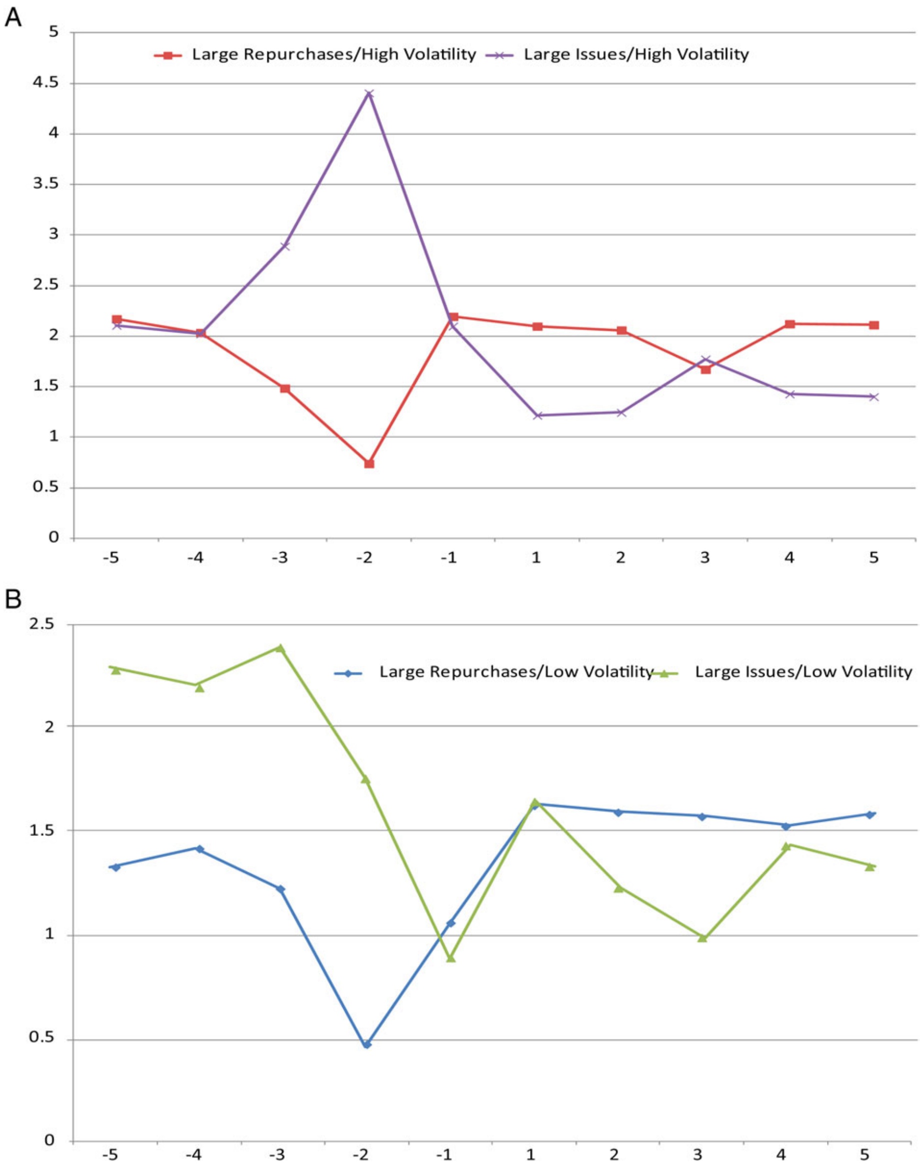


Figure 1. Mean returns of issuance/volatility portfolios in event time. This figure reports average annual raw returns for the equal weighted portfolios of large issues and large repurchases among high (Panel A) and low (Panel B) volatility stocks. Annual returns are expressed on a monthly basis (and in percentage terms) to ease comparison with the numbers reported in the main tables. The x-axis shows years from portfolio formation. Year one, from July of year t through to June of year t+1, is the first year after portfolio formation. Year two, from July of year t+1 through to June of year t+2, is the second year after portfolio formation, and so on.

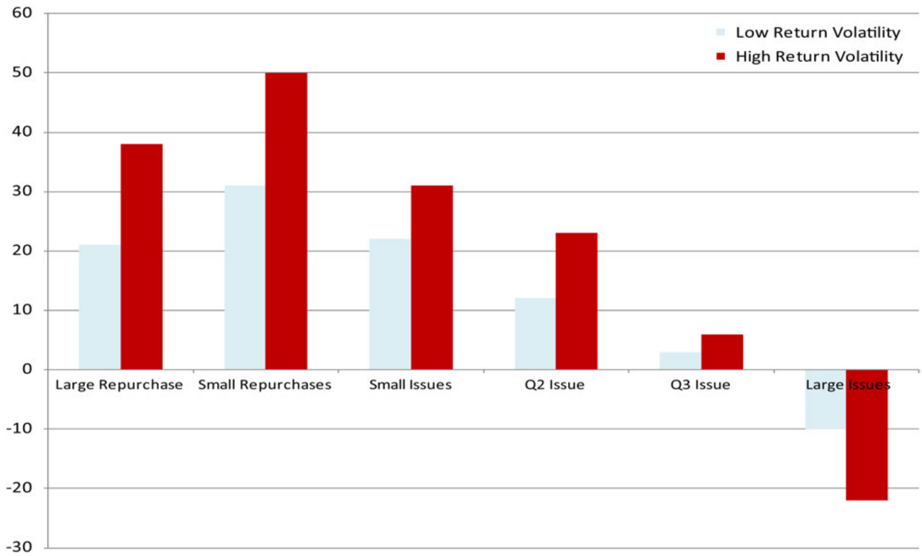


Figure 2. Alphas from three-factor model for issuance/volatility portfolios. This figure shows alphas from regressions of monthly equal-weighted portfolio returns onto the market return, HML, and SMB. Alphas are reported in basis points.

where most high volatility portfolios have higher abnormal returns than low volatility portfolios, except for the case of large issuers.

A related way to study portfolio returns is by running the following time series regression for each portfolio p:

$$R_{pt} - R_{Ft} = \alpha_p + \beta_p(R_{mt} - R_{Ft}) + s_p\,\mathrm{SMB}_t + h_p\,\mathrm{HML}_t + \varepsilon_{pt}, \qquad (13)$$

where the main explanatory variables are the three Fama–French factors downloaded from Ken French's Web site.[16] The constant α captures the abnormal average return for the portfolio. If the Fama–French model is well specified, α is the leftover after cleansing returns for fundamental risk. Table IV reports the regression results for the two extreme portfolios (large repurchases and large issues), the LRMLI portfolios and the difference in LRMLI portfolios. The portfolio of large repurchases produces positive alphas, despite the fact that it is less sensitive to the market factor and SMB. The alpha for the LRMLI portfolio is 0.32% (t-statistic of

[16] SMB and HML factors were downloaded from Ken French's Web site at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

Table IV. Time series regressions of portfolio returns sorted according to issuance activity and return volatility

For the large repurchases and large issues equal-weighted portfolios, we run the following time series regression: $R_{pt}-R_{Ft} = \alpha_p + \beta_p(R_{mt}-R_{Ft}) + s_p$ $\mathrm{SMB}_t + h_p\mathrm{HML}_t + \varepsilon_{pt}$. We also run regressions with the differences between these portfolio returns and the differences across groups of return volatility. We report *t*-statistics below the coefficients.

	Low return volatility portfolios				High return volatility portfolios			
	Alpha	MKtRf	SMB	HML	Alpha	MKtRf	SMB	HML
Large repurchases	**0.21**	0.88	0.58	0.43	**0.38**	1.14	0.94	0.19
	(2.57)	(41.10)	(21.48)	(13.54)	**(3.10)**	(36.07)	(23.50)	(4.11)
Large issues	**−0.10**	1.01	0.83	0.00	**−0.22**	1.22	1.15	−0.44
	(−0.82)	(30.69)	(19.66)	(0.07)	**(−1.36)**	(29.57)	(21.91)	(−7.13)
Large repurchases − large issues (LRMLI)	**0.32**	−0.13	−0.24	0.43	**0.60**	−0.08	−0.21	0.64
	(2.38)	(−3.89)	(−5.51)	(8.35)	**(4.55)**	(−2.40)	(−4.78)	(12.52)
High LRMLI − low LRMLI					**0.28**	0.05	0.03	0.21
					(2.08)	(1.51)	(0.79)	(3.94)

2.38) when return volatility is low and 0.60% (t-statistic of 4.55) when return volatility is high. The difference in LRMLI alphas across return volatility groups is 0.28% (t-statistic of 2.08). The alphas for the six issuance portfolios with high and low return volatility are illustrated in Figure 2.

2.2.b. *Cross-sectional regressions*

Panel regressions with stock-level returns allow us to estimate the marginal effect of issuance and how it varies with return volatility. The regression is of the following form:

$$R_{i,t} = a\,\mathrm{MC}_{i,t-1} + b(B/M)_{i,t-1} + c\,\mathrm{MOM}_{i,t-1} + d\,\mathrm{NEI}_{i,t-1} + \delta_t + \varepsilon_{i,t}. \quad (14)$$

Our coefficient of interest is the effect of net equity issuance on future returns (d). We include standard control variables such as market capitalization (MC), the book-to-market ratio (B/M), and momentum (MOM). As usual, returns from July of year t to June of year $t+1$ are matched with characteristics known in advance. Market capitalization is measured in June of year t. The book-to-market ratio is measured in December of year $t-1$. Net issues are measured over year $t-1$. Momentum is the holding period return from month $j-12$ to month $j-2$. All panel regressions contain month fixed effects (δ_t), and we cluster standard errors by month. The regressions of Fama and MacBeth (1973) give very similar results as reported below. We focus the discussion on the regressions that include momentum since the ones without momentum are very similar.

Regression (14) assumes that the effect of issuance is linear, that is, increasing issues by 1% should have the same effect on returns irrespective of whether the base level of issuing is 0% or 5%. The portfolio sorts, however, suggest that the effect of issuance is nonlinear and driven by extreme issuers. For example, in Table III, more than half of the LRMLI spread comes from the difference between the last two portfolios, Q3 issues and large issues. One can conjecture that being an issuer is a characteristic attached to a stock, and therefore reflected in returns, only after issuance surpasses a given threshold but not continually. In order to explore this possibility, we run the regression with a dummy for large issuers (stocks in the portfolio of "large issues" in Table III) instead of the continuous measure of equity issuance[17]:

$$R_{i,t} = a\,\mathrm{MC}_{i,t-1} + b(B/M)_{i,t-1} + c\,\mathrm{MOM}_{i,t-1} + d\,\mathrm{Issuer}_{i,t-1} + \delta_t + \varepsilon_{i,t} \quad (15)$$

[17] Li, Livdan, and Zhang (2009) use a similar dichotomous variable to capture the cross-sectional effect of issuance in their regressions (see their equation (19), Table 3).

Table V. Cross-sectional regressions of stock returns by groups of return volatility

The table reports coefficients and t-statistics from panel regressions of firm-level stock returns on past variables. The returns to predict are from July of year t to June of year $t+1$. We compute returns over 1 month. The explanatory variables in the regressions are five. MC is the market capitalization computed in June of year t. B/M is the book-to-market ratio of equity computed in December of year $t-1$. Mom (momentum) for month j is the cumulative return from month $j-12$ to month $j-2$. Net issues (net equity issues over total assets) are computed with balance sheet data for year $t-1$. The dummy Issuer has a value of 1 when the stock belongs to the large issues portfolio in Table III and 0 otherwise. Stocks are sorted into groups with high and low return volatility, and the regressions are run separately for each group. For this sort, we first split the sample in five quintiles of market capitalization in June of year t. Then, in each size quintile, we form a high and low group using the median of return volatility within the size quintile. Finally, we pull together the firms with high return volatility from all size quintiles into a single group (identically for firms with low return volatility). All regressions include month fixed effects. All t-statistics are robust and clustered by month. The t-statistic on the difference of coefficients between groups of high and low return volatility corresponds to the t-statistic of the interaction between the variable of interest and a dummy representing the high group in a regression that pools both groups.

	Regression with net equity issues				Regression with issuer dummy					
	MC	*B/M*	Mom	Net issues	MC	*B/M*	Mom	Issuer	# Months	# Observations (in '000s)
High return volatility stocks	−0.32	0.20		**−0.93**	−0.31	0.21		**−0.44**	378	563
	(−5.70)	(2.48)		**(−2.40)**	(−5.51)	(2.39)		**(−3.76)**		
Low return volatility stocks	−0.12	0.03		**−0.54**	−0.12	0.03		**−0.22**	378	566
	(−3.09)	(0.64)		**(−1.13)**	(−2.99)	(0.62)		**(−2.44)**		
High − low	−0.19	0.18		**−0.38**	−0.19	0.18		**−0.22**	378	1,129
	(−6.50)	(2.52)		**(−1.02)**	(−6.39)	(2.51)		**(−2.31)**		
High return volatility stocks	−0.32	0.21	0.36	**−0.87**	−0.32	0.22	0.36	**−0.43**	378	563
	(−5.70)	(2.55)	(1.74)	**(−2.22)**	(−5.59)	(2.50)	(1.75)	**(−3.33)**		
Low return volatility stocks	−0.13	0.02	0.72	**−0.47**	−0.13	0.02	0.72	**−0.19**	378	566
	(−3.23)	(0.49)	(3.67)	**(−0.96)**	(−3.15)	(0.50)	(3.68)	**(−1.57)**		
High − low	−0.19	0.19	−0.37	**−0.39**	−0.19	0.19	−0.37	**−0.24**	378	1,129
	(−6.36)	(2.71)	(−3.60)	**(−1.05)**	(−6.32)	(2.71)	(−3.58)	**(−2.15)**		

In Table V, we show regressions for stocks with high and low return volatility separately, where these groups are defined as in the portfolio sorts. A first thing to note is that the coefficient of net equity issuance is larger in magnitude in the group with high return volatility (-0.87 vs. -0.47). Second, the coefficient is statistically significant only in the group with high return volatility (t-statistic of -2.22 vs. -0.96). However, the difference in the marginal effect of issuance across groups is not significant. The issuer dummy is also significant only among the high volatility stocks (t-statistic of -3.33 vs. -1.57). The coefficient on the issuer dummy can be interpreted as the marginal effect of becoming an issuer on future returns. Among the high volatility stocks, the coefficient implies a loss in future returns of 0.43% monthly, while the effect is only 0.19% among the low volatility stocks. The issuer dummy is significantly different in statistical terms across groups of return volatility (difference of -0.24 with a t-statistic of 2.15).[18] In other words, the marginal effect of being an issuer is significantly stronger among stocks with high volatility.

3.3 PREDICTION 3: RISK DYNAMICS

Carlson, Fisher, and Giammarino (2010) show in their model that there should be a gradual post-issuance decline in the market beta of a stock. This reduction in risk would explain the relatively poor returns of issuers. They find supportive evidence in a sample of 5,700 SEOs between 1980 and 2005. The also find that betas increase before SEOs. We compute market betas for issuers and repurchasers in our sample to see if similar patterns arise within the broader context of the issuance anomaly. Market betas are computed from monthly returns during the previous 12 months. We define the change in beta presorting as the beta computed in December of year $t-1$ (the year of the issuance or repurchase) minus the beta computed in December of year $t-2$. The change in beta postsorting is the beta computed at the time we measure the portfolio return (July of year t up to June of year $t+1$) minus the beta computed in December of year $t-1$. Carlson, Fisher, and Giammarino (2010) also compute long-run changes in betas for up to 3 years after issuance. Our 3-year change in beta postsorting is the beta computed 36 months ahead of the portfolio return minus the beta computed in December of year $t-1$.

In Table VI, and consistent with Carlson, Fisher, and Giammarino (2010), we find that some issuers see their betas increase before the issuance and decline afterward. In particular, for volatile issuers, the change in beta before issuance is 0.23 and it is -0.19 after issuance (-0.25 after 3 years). However, Table VI shows that

[18] The Fama–Macbeth estimate of the differential effect of the issuer dummy across groups of return volatility is -0.19 with a t-statistic of 2.25. The differential effect of net equity issues across groups of return volatility is -0.20 with a t-statistic of 0.48.

Table VI. Average change in betas and t-statistics for firms sorted according to issuance activity and return volatility

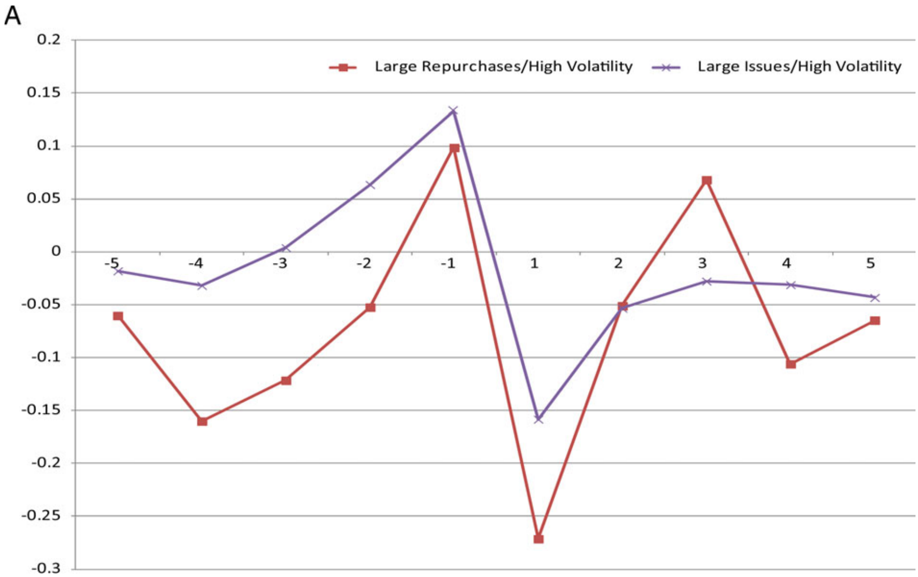
We form six portfolios of issuance activity: large and small repurchases (including zero issuance) plus four quartiles within observations with positive net equity issues. We sort independently into five size (market capitalization in June of year t) quintiles and then within each size quintile into high and low values of return volatility or sentiment betas. Finally, we pull together observations for high and low values of the sorting variable across size quintiles. Within each one of the twelve resulting portfolios, we compute average changes in market betas presorting and postsorting (i.e., pre- and post-portfolio formation). Betas are computed from a regression of monthly returns during the previous 12 months onto the market return, SMB, or HML, respectively. We define the change in beta presorting as the difference in betas computed in December of year $t-1$ (the year of the issuance or repurchase) and December of year $t-2$. The change in beta postsorting is the difference in betas computed at the time we measure the portfolio return (July of year t up to June of year $t+1$) and December of year $t-1$. The change in beta postsorting with 3 years is the difference in betas computed 36 months ahead of the portfolio return and December of year $t-1$.

	Low and high values of return volatility											
	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
	Average change in beta (pre)		t-statistics		Average change in beta (post)		t-statistics		Average change in beta (post, 3 years)		t-statistics	
(A) Changes in market betas												
Large repurchases	−0.19	0.27	−16.79	11.56	0.11	−0.27	7.72	−12.37	0.21	−0.31	12.85	−13.96
Small repurchases	−0.21	0.26	−16.16	11.77	0.11	−0.27	8.53	−11.94	0.20	−0.29	11.07	−11.59
Small issues	−0.21	0.22	−15.33	10.51	0.11	−0.26	7.89	−11.46	0.19	−0.32	9.89	−12.86
Q2 issues	−0.21	0.27	−17.71	13.46	0.15	−0.26	11.92	−12.67	0.19	−0.36	11.64	−15.76
Q3 issues	−0.23	0.26	−19.08	14.15	0.17	−0.23	13.03	−10.90	0.21	−0.34	12.66	−16.60
Large issues	−0.34	0.23	−17.31	9.23	0.31	−0.19	16.27	−7.18	0.33	−0.25	15.81	−8.83
Large repurchases − large issues (LRMLI)	0.15	0.04	8.95	2.49	−0.20	−0.08	−14.26	−5.96	−0.12	−0.06	−8.83	−3.08
High LRMLI − low LRMLI		−0.11		−7.27		0.12		9.33		0.06		3.27

Continued

Table VI. Continued

	Low and high values of return volatility											
	Low	High	Low	High	Low	High	Low	High	Low	High	Low	High
	Average change in beta (pre)		*t*-statistics		Average change in beta (post)		*t*-statistics		Average change in beta (post, 3 years)		*t*-statistics	
(B) Changes in SMB betas												
Large repurchases	−0.25	0.29	−5.63	4.70	0.10	−0.38	2.31	−5.76	0.15	−0.58	3.24	−8.26
Small repurchases	−0.24	0.32	−5.45	5.29	0.12	−0.43	3.16	−6.78	0.09	−0.55	2.08	−7.91
Small issues	−0.24	0.23	−5.90	3.78	0.08	−0.41	1.94	−6.81	0.11	−0.56	2.51	−8.12
Q2 issues	−0.25	0.23	−5.27	3.62	0.09	−0.33	2.00	−5.06	0.10	−0.46	2.14	−6.84
Q3 issues	−0.28	0.29	−5.83	4.41	0.14	−0.38	3.18	−5.82	0.13	−0.52	2.54	−7.55
Large issues	−0.51	0.28	−10.01	3.96	0.26	−0.45	5.60	−6.73	0.24	−0.54	4.76	−7.06
Large repurchases − large issues (LRMLI)	0.26	0.02	12.78	0.62	−0.17	0.06	−8.68	2.46	−0.10	−0.04	−4.89	−1.15
High LRMLI − low LRMLI		−0.24		−10.45		0.23		11.02		0.06		1.94
(C) Changes in HML Betas												
Large repurchases	0.13	−0.13	2.90	−1.92	−0.12	0.08	−2.82	1.16	−0.24	0.11	−5.58	1.43
Small repurchases	0.11	−0.12	2.32	−1.83	−0.13	−0.04	−3.02	−0.51	−0.22	−0.03	−4.61	−0.37
Small issues	0.15	−0.17	3.10	−2.39	−0.15	0.01	−3.25	0.19	−0.20	0.09	−4.17	1.11
Q2 issues	0.18	−0.12	3.64	−1.85	−0.20	0.04	−4.51	0.57	−0.20	0.19	−4.33	2.54
Q3 issues	0.24	−0.16	5.09	−2.32	−0.20	0.04	−4.56	0.61	−0.15	0.23	−3.17	3.01
Large issues	0.26	−0.16	5.05	−2.34	−0.27	0.02	−6.15	0.25	−0.26	0.21	−5.68	2.67
Large repurchases − large issues (LRMLI)	−0.12	0.03	−6.65	1.11	0.16	0.06	9.26	2.45	0.02	−0.10	1.00	−2.73
High LRMLI − low LRMLI		0.16		5.95		−0.09		−3.96		−0.12		−3.61



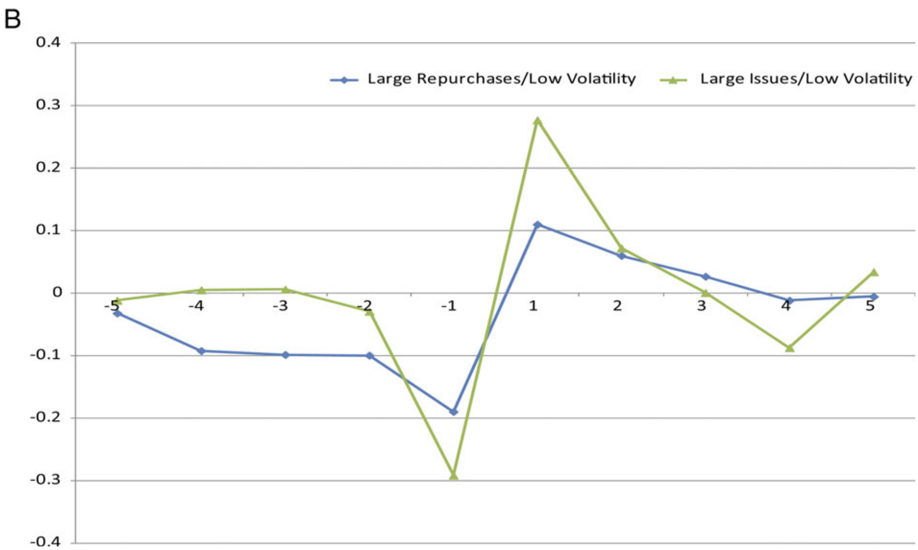


Figure 3. Average changes in market betas of issuance/volatility portfolios in event time. This figure reports average annual changes in market betas for the portfolios of large issues and large repurchases among high (Panel A) and low (Panel B) volatility stocks. The x-axis shows years from portfolio formation. Year one, from July of year *t* through to June of year *t*+1, is the first year after portfolio formation. Year two, from July of year *t*+1 through to June of year *t*+2, is the second year after portfolio formation, and so on.

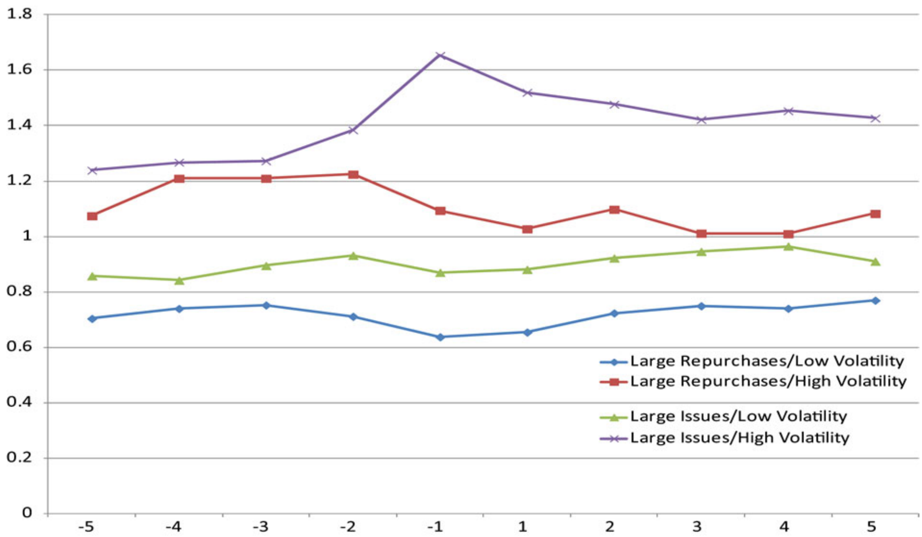


Figure 4. Average share turnover of issuance/volatility portfolios in event time. This figure reports average monthly share turnover for the portfolios of large issues and large repurchases among high and low volatility stocks. The x-axis shows years from portfolio formation. Year 1, from July of year t to June of year $t + 1$, is the 1st year after portfolio formation. Year 2, from July of year $t + 1$ to June of year $t + 2$, is the 2nd year after portfolio formation, and so on.

this pattern is really an artifact of the volatility sorting rather than issuance. All high volatility stocks, regardless of whether they issue or repurchase, present a similar pattern of changes in beta. Volatile issuers and repurchasers alike see their betas decline into the future, therefore, the change in beta cannot be the reason for the return spread generated between them. If anything, volatile repurchasers see their betas decline by more than volatile issuers, which would be inconsistent with their higher returns. The opposite pattern of changes in betas is seen in low volatility stocks: declines in betas presorting and increases in betas postsorting. Figure 3 summarizes these dynamics of market betas in event time around portfolio formation. As in Figure 1 for returns, and for visual clarity, we present averages of annual changes, but the message is the same as in Table VI. Figure 4 shows share turnover for the portfolios in the previous figure to see the extent to which liquidity mirrors the dynamics of beta. There is little change in the turnover of low volatility stocks throughout the issuance–repurchase period. For high volatility issuers, there is an increase in turnover 2 years before issuance that is only slightly reversed after issuance, but less violently than what is seen in market betas. High volatility repurchasers experience a fall in turnover before repurchasing, but it does not reverse after repurchase. Overall, beta dynamics and liquidity dynamics do not seem to mirror each other closely.

Table VII. Cross-sectional regressions of changes in market betas postsorting by groups of return volatility

The table reports coefficients and t-statistics from panel regressions of changes in market betas on past variables. Market betas are computed from monthly returns during the previous 12 months. The changes in beta to predict correspond to the difference in betas computed at the time we measure the portfolio return (July of year t up to June of year $t+1$) and December of year $t-1$. The explanatory variables in the regressions are five. Investment over assets is the ratio of capital expenditures over total book assets in December of year $t-1$. The dummy Issuer has a value of 1 when the stock belongs to the large issues portfolio in Table III and 0 otherwise. MC is the market capitalization computed in June of year t. B/M is the book-to-market ratio of equity computed in December of year $t-1$. Mom (momentum) for month j is the cumulative return from month $j-12$ to month $j-2$. Stocks are sorted into groups with high and low return volatility, and the regressions are run separately for each group. For this sort, we first split the sample in five quintiles of market capitalization in June of year t. Then, in each size quintile, we form a high and low group using the median of return volatility within the size quintile. Finally, we pull together the firms with high return volatility from all size quintiles into a single group (identically for firms with low return volatility). All regressions include month fixed effects. All t-statistics are robust and clustered by month. The t-statistic on the difference of coefficients between groups of high and low return volatility corresponds to the t-statistic of the interaction between the variable of interest and a dummy representing the high group in a regression that pools both groups.

	Dependent variable in regression: change in equity beta postsorting											
	Low and high values of return volatility											
	Low	High	H-L	Low	High	H-L	Low	High	H-L	Low	High	H-L
Investment over assets	0.019	0.089	0.070							−0.033	0.147	0.180
	(0.43)	(1.20)	(1.07)							(−0.72)	(2.10)	(2.96)
Issuer				0.157	0.072	−0.085				0.144	0.056	−0.088
				(14.44)	(6.47)	(−8.74)				(14.48)	(6.10)	(−9.15)
MC							−0.009	0.004	0.013	−0.007	0.006	0.013
							(−2.66)	(0.72)	(4.19)	(−2.00)	(1.21)	(4.41)
B/M							−0.042	−0.041	0.001	−0.041	−0.042	−0.001
							(−8.74)	(−4.52)	(0.16)	(−8.57)	(−4.82)	(−0.17)
Mom							0.204	0.211	0.007	0.204	0.211	0.007
							(10.15)	(10.47)	(0.55)	(9.84)	(10.39)	(0.53)
# Observations	623,773	622,564	1,246,337	574,202	578,874	1,153,076	622,120	611,117	1,233,237	558,014	553,222	1,111,236
R-squared	0.04	0.05	0.06	0.04	0.05	0.06	0.05	0.05	0.07	0.05	0.05	0.06

The results in Table VI have implications for how to choose benchmarks for issuers in other applications. For instance, Carlson, Fisher, and Giammarino (2010) compute changes in the market betas of issuers relative to changes in a benchmark stock. The benchmark is a nonissuer, which is similar to the issuer in terms of its book-to-market ratio and size. If inadvertently the nonissuer is in a different volatility category, then changes in betas can be exaggerated. For example, the change in beta for a high volatility issuer minus the change in beta for a low volatility nonissuer can be particularly large. More importantly, those changes in betas would not be necessarily related to the return spread that one tries to explain.

We also compute changes in betas with respect to other risk factors used in the empirical asset pricing literature, namely SMB and HML of Fama and French (1993). Changes in SMB betas follow similar dynamics as market betas. Again, volatile repurchasers and issuers alike experience a reduction in the loading to this risk factor after the portfolio sorting. The dynamics of HML betas are slightly different. Volatile stocks experience a decrease in HML betas presorting and an increase postsorting. According to this, volatile repurchasers and issuers would become more risky after issuance. Unfortunately, since a similar change applies across all portfolios it is unlikely that it can explain the large return spread between the extremes. Also, if we focus on the magnitude of the changes, these are unlikely to explain large changes in expected returns. For example, the portfolio of large repurchases experiences an increase in HML beta of only 0.08 postsorting (0.11 at the 3-year horizon). Given that the return premium attached to HML is on the order of 0.50%, this change in HML beta would imply a change in expected returns of only a few basis points.

In order to understand the marginal determinants of changes in betas, we run panel regressions with the change in market beta as dependent variable in Table VII. The regressions are analogous to the regressions with returns in Equation (14), all of them containing time fixed effects and the same lags as in return regressions. Carlson, Fisher, and Giammarino (2010) run similar regressions within their sample of SEOs, although we include all stocks and not only issuers. A key finding in Carlson, Fisher, and Giammarino (2010) is the negative effect of investment on future betas. We find instead that investment has a positive effect on future betas (coefficient 0.147, t-statistic 2.10). More to the point of the issuance anomaly, we find a positive and statistically significant coefficient on the issuer dummy. This means that issuers on average see their betas increase when compared to other stocks in the same volatility group, as can be expected from the average changes in beta reported in Table VI. The increase is smaller among volatile stocks (the differential effect is -0.088, t-statistic -9.15).

Table VIII reports similar regressions for the 3-year change in market beta and for the changes in HML and SMB betas. The investment rate has a positive impact

Table VIII. Cross-sectional regressions of changes in risk-factor betas postsorting by groups of return volatility

The table reports coefficients and t-statistics from panel regressions of changes in risk factor betas on past variables. Betas are computed from a regression of monthly returns during the previous 12 months onto the market return, SMB, or HML, respectively. In the case of SMB and HML, the change in beta to predict correspond to the difference in betas computed at the time we measure the portfolio return (July of year t up to June of year $t+1$) and December of year $t-1$. In the case of market betas, it corresponds to the difference in betas computed 36 months ahead of the portfolio return and December of year $t-1$. The explanatory variables in the regressions are five. Investment over assets is the ratio of capital expenditures over total book assets in December of year $t-1$. The dummy Issuer has a value of 1 when the stock belongs to the large issues portfolio in Table III and 0 otherwise. MC is the market capitalization computed in June of year t. B/M is the book-to-market ratio of equity computed in December of year $t-1$. Mom (momentum) for month j is the cumulative return from month $j-12$ to month $j-2$. Stocks are sorted into groups with high and low return volatility, and the regressions are run separately for each group. For this sort, we first split the sample in five quintiles of market capitalization in June of year t. Then, in each size quintile, we form a high and low group using the median of return volatility within the size quintile. Finally, we pull together the firms with high return volatility from all size quintiles into a single group (identically for firms with low return volatility). All regressions include month fixed effects. All t-statistics are robust and clustered by month. The t-statistic on the difference of coefficients between groups of high and low return volatility corresponds to the t-statistic of the interaction between the variable of interest and a dummy representing the high group in a regression that pools both groups.

	Dependent variable in regression: change in beta postsorting								
	Market beta (3 years)			SMB beta			HML beta		
	Low and high values of return volatility								
	Low	High	H-L	Low	High	H-L	Low	High	H-L
Investment over assets	0.132	0.169	0.038	−0.051	0.219	0.271	0.154	−0.217	−0.371
	(2.26)	(2.02)	(0.52)	(−0.91)	(2.09)	(3.05)	(2.03)	(−1.73)	(−3.04)
Issuer	0.117	0.077	−0.040	0.127	−0.024	−0.152	−0.070	−0.004	0.066
	(12.46)	(6.19)	(−3.07)	(9.43)	(−1.65)	(−10.18)	(−4.88)	(−0.25)	(4.57)
MC	−0.022	−0.025	−0.003	−0.039	0.055	0.094	0.023	0.018	−0.005
	(−6.19)	(−5.17)	(−0.94)	(−8.69)	(7.98)	(20.25)	(4.54)	(1.83)	(−0.76)
B/M	−0.015	−0.008	0.007	−0.047	0.049	0.096	0.061	0.006	−0.056
	(−3.00)	(−0.90)	(0.82)	(−7.39)	(3.95)	(10.34)	(10.15)	(0.42)	(−4.83)
Mom	0.137	0.117	−0.020	0.249	0.250	0.001	−0.158	−0.153	0.005
	(12.72)	(7.63)	(−1.62)	(9.11)	(8.70)	(0.08)	(−4.35)	(−4.08)	(0.31)
# Observations	396,812	368,426	765,238	558,014	553,222	1,111,236	558,014	553,222	1,111,236
R-squared	0.06	0.05	0.08	0.17	0.17	0.18	0.16	0.15	0.16

on the market beta of high and low volatility stocks. The effect of the issuer dummy is also positive and statistically significant, although smaller in magnitude among the high volatility stocks (the differential effect is -0.04, *t*-statistic -3.07). The regressions for SMB and HML betas show that volatile issuers experience a decline in these betas when compared to other volatile stocks, although the effect is not statistically significant.

Overall, the results in Tables VII and VIII show that issuers, and in particular volatile issuers, do not experience a clear fall in betas after issuance when compared to other stocks in the same volatility group. We can conjecture about the reasons for the differences between our results and those in Carlson, Fisher, and Giammarino (2010). First, there are sample differences: they focus only on SEOs and during a slightly shorter time period.[19] Second, and more importantly, for each SEO, they choose a benchmark non-SEO firm based on size and *B/M*. Changes in betas for an SEO firm are compared with changes in beta for the benchmark firm, and this double difference is used as dependent variable in regressions similar to those in our Table VII. Our findings suggest that results can be misleading if the benchmark firm is in another volatility group. Our Table VII represents an alternative albeit implicit way of picking a benchmark by letting the regression determine the differential effect between issuers and nonissuers after controlling for size, *B/M*, and other firm characteristics.

Carlson, Fisher, and Giammarino (2010) note that the same patterns in market betas that are predicted by the real options theory are also predicted by a theory of aggregate sentiment. On the contrary, idiosyncratic sentiment does not predict changes in market betas. Any idiosyncratic movement in prices is, by definition, not reflected in a market beta, which captures comovement with the rest of the market. The fact that we do not find the dynamics of market betas predicted by aggregate sentiment suggests that aggregate sentiment cannot be the main driver of the issuance anomaly. In other words, if we are still to pursue a behavioral explanation this explanation, by default, needs to rest on idiosyncratic sentiment as the source of mispricing. Although this is a potential way out for the behavioral explanation, it is hard to identify idiosyncratic sentiment empirically. So far we only have indirect ways to differentiate idiosyncratic and aggregate sentiment by looking at the dynamics of market betas.

2.4 PREDICTION 4: SENTIMENT VOLATILITY

Baker and Wurgler (2007) show that more volatile stocks have higher sensitivity to an index of aggregate sentiment developed in their earlier work (see Baker and

[19] Also their SEO sample is a selection of the entire SEO universe in the US market. For example, Pontiff and Woodgate (2008) report that there are 14,556 SEOs in the USA between 1971 and 2003.

Table IX. Correlation matrix of return volatility and sentiment betas

Variable definitions are provided in the main text and the Appendix. All variables are winsorized at the 1% and 99% levels.

	Return Volatility	Beta with sentiment (1)	Beta with sentiment (2)	Beta with sentiment (3)	Beta with sentiment (4)
Return volatility	1.00				
Beta with sentiment (1)	0.32	1.00			
Beta with sentiment, market adjusted (2)	0.31	0.90	1.00		
Beta with orthogonal sentiment (3)	0.28	0.52	0.54	1.00	
Beta with orthogonal sentiment, market adjusted (4)	0.26	0.49	0.56	0.96	1.00

Table X. Average returns and *t*-statistics for LRMLI portfolios according to proxies for sentiment volatility and equity dependence

We form six portfolios of issuance activity: large and small repurchases (including zero issuance) plus four quartiles within observations with positive net equity issues. We sort independently into five size (market capitalization in June of year *t*) quintiles and then within each size quintile into high and low values of the sorting variable. Finally, we pull together observations for high and low values of the sorting variable across size quintiles. Within each one of the twelve resulting portfolios, we compute equal-weighted returns each month. This table shows the average return across months for the portfolio that is long in large repurchases (LRs) and short in large issues (LIs), which we call the LRMLI portfolio. Size- and *B*/*M*-adjusted returns subtract from the raw return of each firm the return of a benchmark portfolio based on independent sorts into size and book-to-market NYSE quintiles (for details, see Fama and French 2008). Average returns are multiplied by 100.

	Low and high values of sorting variable					
	Low	High	H-L	Low	High	H-L
Sorting variable	Average returns (LRMLI portfolio)			*t*-statistics		
(A) Baker–Wurgler sentiment measures						
Beta with sentiment	0.01	0.23	0.22	0.06	1.36	1.28
Beta with orthogonal sentiment	0.00	0.24	0.25	−0.02	1.43	1.43
Beta with sentiment, market adjusted	0.01	0.21	0.20	0.06	1.23	1.29
Beta with orthogonal sentiment, market adjusted	0.00	0.23	0.23	−0.02	1.33	1.48
(B) Measures of equity dependence						
KZ index	0.19	0.15	−0.04	1.02	0.87	−0.31
Standard deviation analysts' forecasts	0.32	0.39	0.07	1.49	1.66	0.38

Wurgler, 2006). The sentiment index is a composite of six variables, including the average closed-end fund discount, IPO underpricing, market turnover, and others. Their finding implies that some volatile stocks have more volatile returns partly because they react more to common sentiment shocks that affect the whole market. Similar to Baker and Wurgler (2006), we compute the sentiment beta of each stock by running a regression of monthly stock returns from January to December of each year on changes in the sentiment index.[20] We also compute a market-adjusted sentiment beta by running the same regression with market-adjusted stock returns as dependent variable.

Table IX reports correlations of sentiment betas with return volatility. The correlations are positive but not perfect. An average correlation with return volatility of 0.30 across the different measures of sentiment beta implies that there is still significantly independent movements in stock returns that are not associated with aggregate sentiment. This is perhaps not surprising given that the lion's share of volatility is idiosyncratic (see Campbell *et al.*, 2001). The correlation between sentiment betas and market-adjusted sentiment betas is quite high (around 0.90). In Table IX, we also report betas with orthogonal sentiment, which are betas with respect to a version of the index of Baker and Wurgler (2006) that is orthogonal to macroeconomic fluctuations.

Table X reports average LRMLI spreads for stocks of high and low sentiment betas. The sorting procedure is the same as with return volatility in Table III. We report size- and *B*/*M*-adjusted returns of equal-weighted portfolios. The average LRMLI spread among stocks with high sentiment beta is 0.23% (*t*-statistic 1.36), while it is only 0.01% (*t*-statistic 0.06) among stocks with low sentiment betas. The difference in LRMLI spreads of 0.22% (*t*-statistic 1.28) is half the size of the difference between volatility-sorted portfolios (0.44% in Table III), and it is not statistically significant. The results are similar using other measures of sentiment beta. While the direction of the effects is the same as with volatility sorts, the magnitude and statistical significance are smaller.

Baker, Stein, and Wurgler (2003) note that firms that are more equity dependent may be more sensitive to irrational fluctuations in stock prices. In other words, equity dependent firms may base their issuance decisions closely following swings in market sentiment. In order to test for this related hypothesis, we compute average returns for LRMLI portfolios using standard proxies for equity dependence in Table X. Although the correlations shown in Table I are small, it could be the case that volatility is associated with proxies of equity dependence such as the KZ index or the cross-analyst standard deviation of EPS forecasts (i.e., the proxy for disagreement in Dittmar and Thakor (2007)). We find that the LRMLI spread is about the same magnitude among stocks that are equity dependent and among other stocks.

[20] We thank Jeff Wurgler for making available the sentiment index data through his Web site.

Table XI. Average returns and t-statistics for LRMLI portfolios conditional on sentiment levels

We form six portfolios of issuance activity: large and small repurchases (including zero issuance) plus four quartiles within observations with positive net equity issues. We sort independently into five size (market capitalization in June of year t) quintiles and then within each size quintile into high and low values of return volatility or sentiment betas. Finally, we pull together observations for high and low values of the sorting variable across size quintiles. Within each one of the twelve resulting portfolios, we compute equal-weighted returns each month. This table shows the average return for the portfolio that is long in large repurchases (LRs) and short in large issues (LIs), which we call the LRMLI portfolio. Size- and B/M-adjusted returns subtract from the raw return of each firm the return of a benchmark portfolio based on independent sorts into size and book-to-market NYSE quintiles (for details, see Fama and French 2008). Average returns are multiplied by 100. We split firms in two groups according to whether the index of aggregate sentiment of Baker and Wurgler (2006) was positive or negative at the time of issuance (i.e., at the time of portfolio formation).

	Average Returns				t-statistics			
	Large repurchasers	Large issues	LRMLI	H-L LRMLI	Large repurchaser	Large issues	LRMLI	H-L LRMLI
(A) Sorting variable: return volatility								
High (H) return volatility stocks								
After negative sentiment	0.39	−0.04	0.44	**0.85**	2.53	−0.24	2.27	**3.98**
After positive sentiment	0.45	0.11	0.35	**0.24**	2.55	0.38	1.72	**1.15**
Low (L) return volatility stocks								
After negative sentiment	−0.05	0.36	−0.41		−0.52	2.13	−2.14	
After positive sentiment	0.10	−0.01	0.11		0.79	−0.08	0.52	
(B) Sorting variable: sentiment beta								
High (H) sentiment beta stocks								
After negative sentiment	0.17	−0.12	0.28	**0.47**	1.33	−0.60	1.46	**2.14**
After positive sentiment	0.31	0.11	0.20	**0.09**	2.12	0.37	0.86	**0.39**
Low (L) sentiment beta stocks								
After negative sentiment	0.10	0.29	−0.19		0.97	1.62	−0.90	
After positive sentiment	0.18	0.07	0.11		1.57	0.32	0.46	

This suggests that the equity dependence effect is not the same as the volatility effect, and in particular, it is not the case that high equity dependence is associated with large LRMLI spreads.

In Table XI, we use the level of the sentiment index of Baker and Wurgler (2006) as a conditioning variable. We ask whether the LRMLI spread depends on the aggregate level of sentiment at the time of issuance or repurchase. This exercise is similar to what Baker and Wurgler (2006) do to understand the conditional behavior of other anomalies, although they do not examine the issuance anomaly. We find that repurchasers strongly outperform issuers among the high volatility stocks after periods of negative sentiment: the LRMLI spread is 0.44% (*t*-statistic 2.27). After periods of positive sentiment, the LRMLI among high volatility stocks is smaller (0.35%, *t*-statistic 1.72). The results among low volatility stocks are quite different: following negative sentiment the LRMLI spread reverses (i.e., it turns negative), and it is close to zero after positive sentiment. The difference in LRMLI spreads between more and less volatile stocks is large and statistically significant after negative sentiment (0.85%, *t*-statistic 3.98) but small and not statistically significant after positive sentiment (0.24%, *t*-statistic 1.15). Therefore, the issuance anomaly comes mostly from volatile stocks, as seen in our previous tables, and it is relatively stronger after periods of negative sentiment. Among the less volatile stocks, the anomaly is reversed after periods of depressed aggregate sentiment. This is further proof that the issuance anomaly (i.e., positive repurchaser–issuer spreads) is concentrated in stocks of high sentiment volatility.

Although the unconditional effects of sentiment betas are not significant in Table X, we do find significant effects of sentiment betas once we condition on the level of market sentiment in Table XI. The difference in LRMLI spreads between stocks with high and low sentiment betas is large and statistically significant after negative sentiment (0.47%, *t*-statistic 2.14) but small and not statistically significant after positive sentiment (0.09%, *t*-statistic 0.39). The magnitudes are still smaller than those seen in the volatility sorts in the top panel of Table XI. The issuance anomaly is basically absent among low sentiment beta stocks.

When comparing our results to those in Baker and Wurgler (2006), we see that the issuance anomaly is not the only anomaly that is relatively stronger following negative sentiment. For instance, a similar pattern is observed in the size anomaly: small stocks have high returns compared to large stocks following negative sentiment but not following positive sentiment. Our portfolios are all size-balanced, so our results are not simply relabeling this conditional effect of the size anomaly. Conditioning on the level of sentiment appears to be crucial among low volatility (beta) stocks, although not so much among high volatility (beta) stocks. Among low volatility stocks, the issuance anomaly reverses following periods of negative sentiment with issuers earning large positive returns. This flip in the sign of the anomaly is not exclusive to low volatility issuers. For example, Baker and Wurgler

Table XII. Time series regressions of portfolio returns sorted according to issuance activity and return volatility: conditioning on sentiment levels

For the large repurchases (LRs) and large issues (LIs) equal-weighted portfolios, we run the following time series regressions: $R_{pt}-R_{Ft} = \alpha_p + d_p\ \mathrm{Sent}_{t-1} + \beta_p(R_{mt}-R_{Ft}) + s_p\mathrm{SMB}_t + h_p\mathrm{HML}_t + \varepsilon_{pt}$, and $R_{pt}-R_{Ft} = \alpha_p + [e_p + \mathrm{Sent}_{t-1}]x[\beta_p(R_{mt}- R_{Ft}) + s_p\ \mathrm{SMB}_t + h_p\ \mathrm{HML}_t] + \varepsilon_{pt}$.The variable Sent_{t-1} corresponds to the average of the Baker–Wurgler index of market sentiment over the previous year (the year of portfolio formation). In the case of the 2nd regression, we only report in this table the coefficients of sentiment interacted with the market return, SMB, and HML. Besides the LR and LI portfolios, we also run regressions with the differences between these portfolio returns and the differences across groups of return volatility. We report *t*-statistics below the coefficients.

	Low return volatility portfolios					High return volatility portfolios				
	Alpha	Sent	MKtRf	SMB	HML	Alpha	Sent	MKtRf	SMB	HML
Large repurchases − large issues (LRMLI)	**0.32**	0.02	−0.13	−0.24	0.43	**0.60**	−0.01	−0.08	−0.21	0.64
	(2.38)	(0.12)	(−3.87)	(−5.50)	(8.33)	**(4.53)**	(−0.04)	(−2.39)	(−4.74)	(12.49)
High LRMLI − low LRMLI						**0.28**	−0.02	0.05	0.04	0.21
						(2.07)	(−0.15)	(1.51)	(0.82)	(3.95)
Large repurchases − large issues (LRMLI)	**0.31**		−0.08	−0.12	0.03	**0.59**		−0.09	−0.12	−0.03
	(2.36)		(−2.14)	(−1.97)	(0.41)	**(4.52)**		(−2.45)	(−2.03)	(−0.53)
High LRMLI − low LRMLI						**0.28**		−0.01	0.00	−0.06
						(2.03)		(−0.27)	(−0.03)	(−0.91)

(2006) find that the relative returns of dividend payers versus nonpayers and profitable versus unprofitable firms are positive after positive sentiment but negative after negative sentiment.

In Table XII, we run conditional factor models using the sentiment index as conditional variable (for a similar approach, see Baker and Wurgler, 2006). More specifically, we run a regression that is an extension of regression (13):

$$R_{pt} - R_{Ft} = \alpha_p + \left[e_p + \mathrm{Sent}_{t-1}\right]\left[\beta_p(R_{mt} - R_{Ft}) + s_p\,\mathrm{SMB}_t + h_p\,\mathrm{HML}_t\right] + \varepsilon_{pt}. \tag{16}$$

The variable Sent_{t-1} is the average level of sentiment in the year before portfolio formation (January–December of year $t-1$). We also report the regression where the sentiment level is simply added as an extra factor, that is, without the interaction with the market return, SMB, or HML:

$$R_{pt} - R_{Ft} = \alpha_p + d_p\,\mathrm{Sent}_{t-1} + \beta_p(R_{mt} - R_{Ft}) + s_p\,\mathrm{SMB}_t + h_p\,\mathrm{HML}_t + \varepsilon_{pt}. \tag{17}$$

The results in Table XII show that conditioning on sentiment has little impact on the results. Alphas are of almost the same magnitude and statistical significance as seen in Table IV.

4. Conclusions

This paper studies the relationship between equity issues and return volatility in order to shed light on the motives behind the issuance anomaly. We find that the negative effect of equity issuance on future returns is relatively stronger among stocks with high return volatility. Rational and behavioral theories predict that this finding is the product of risk volatility and sentiment volatility, respectively. However, our results are inconsistent with these theories as they currently stand. Loadings on standard risk factors such as the market return, SMB, and HML do not follow the dynamics that would explain the return predictability related to issuance decisions. If we sort on a stock's beta with respect to the aggregate sentiment index of Baker and Wurgler (2006), which proxies for sentiment volatility, the results are weaker—economically and statistically—than when sorting on return volatility. If rational models are to explain the issuance anomaly they probably need to address new risk factors, while behavioral models probably need to focus on idiosyncratic sentiment and on how to identify it empirically.

Supplementary Material

Supplementary data are available at *Review of finance* online.

Appendix

MODEL DETAILS

Solving the 1st order condition of the manager's problem, we find that equilibrium prices and issuance are given by

$$P_1 = \underbrace{\frac{1}{2}}_{a_0} + \underbrace{(\frac{1}{2} - \alpha)\frac{\rho_F}{\rho}}_{a_1} F + \underbrace{\frac{(1-\alpha)\rho_F}{2\rho}}_{a_2} S - \underbrace{\frac{(1-\alpha)^2 Q_0}{2\rho}}_{a_3} \gamma, \tag{A1}$$

$$Q_1 = -\underbrace{\frac{Q_0}{2}}_{b_0} + \frac{1}{\gamma}\left[\underbrace{\frac{\rho_F}{2(1-\alpha)^2}}_{b_1} F + \underbrace{\frac{\rho_F}{2(1-\alpha)}}_{b_2} S - \underbrace{\frac{\rho}{2(1-\alpha)^2}}_{b_3}\right]. \tag{A2}$$

DEFINITION OF CAPITAL STRUCTURE VARIABLES

Variable definitions are taken from Kayhan and Titman (2007) when available. Annual Compustat item numbers are provided after the definition. The definition of the KZ index is taken from Baker, Stein, and Wurgler (2003).

1. Book equity = total assets − total liabilities − preferred stock + deferred taxes + convertible debt = data6 − data181 − data10 + data35 + data79.
2. Net equity issues/assets = (change in book equity − change in retained earnings)/total assets = (Δbook equity −Δdata36)/data6.
3. Net equity issues (cash flow measure) = sale of common and preferred stock − purchase of common and preferred stock = data108 − data115.
4. Market equity = common shares outstanding × price = data25 × data199.
5. Market-to-book ratio of assets = market assets/book assets = (data6 − book equity + market equity)/data6.

6. Return on assets (ROAs) = earnings before interest, tax, and depreciation/total assets = data13/data6.
7. ROA volatility = standard deviation of ROA in the past 3 years.
8. Book debt = total assets − book equity = data6 − book equity.
9. Book leverage = book debt/total assets = book debt/data6.
10. Sales = logarithm of sales = ln(data12).
11. Tangibility = net property, plant, and equipment/total assets = data8/data6.
12. Cash balance = cash/total assets = data1/data6.
13. Dividends = total dividends/total assets = (data19 + data 21)/data6.
14. Kaplan–Zingales Cash Flow (CF) = (data14+data18)/lagged data6.
15. Kaplan–Zingales Dividends (Div) = (data19+data21)/lagged data6.
16. Kaplan–Zingales Cash Stock (C) = data1/lagged data6.
17. Kaplan–Zingales Leverage (Lev) = (data9 + data34)/(data9 + data34 + data216).
18. Kaplan–Zingales Index = −1.002 CF − 39.368 Div − 1.315 C + 3.139 Lev.
19. Investment over assets = capital expenditure/total assets.

References

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

Baker, M. P., Coval, J., and Stein, J. C. (2007) Corporate financing decisions when investors take the path of least resistance, *Journal of Financial Economics* **84**, 266–298.

Baker, M. P., Stein, J. C., and Wurgler, J. A. (2003) When does the stock market matter? Stock prices and the investment of equity-dependent firms, *Quarterly Journal of Economics* **118**, 969–1005.

Baker, M. P. and Wurgler, J. A. (2000) The equity share in new issues and aggregate stock returns, *Journal of Finance* **55**, 2219–2257.

Baker, M. P. and Wurgler, J. A. (2006) Investor sentiment and the cross-section of stock returns, *Journal of Finance* **61**, 1645–1680.

Baker, M. P. and Wurgler, J. A. (2007) Investor sentiment in the stock market, *Journal of Economic Perspectives* **21**, 129–151.

Bali, T. G., Ozgur Demirtas, K., and Hovakimian, A. (2010) Corporate financing activities and contrarian investment, *Review of Finance* **14**, 543–584.

Banerjee, S. and Kremer, I. (2010) Disagreement and learning: Dynamic patterns of trade, *Journal of Finance* **65**, 1269–1302.

Brav, A., Heaton, J. B., and Li, S. (2010) The limits of the limits to arbitrage, *Review of Finance* **14**, 157–187.

Campbell, J. Y. (1991) A variance decomposition for stock returns, *Economic Journal* **101**, 157–179.

Campbell, J. Y. and Cochrane, J. H. (1999) By force of habit: A consumption-based explanation of aggregate stock market behavior, *Journal of Political Economy* **107**, 205–251.

Campbell, J. Y., Lettau, M., Malkiel, B., and Xu, Y. (2001) Have individual stocks become more volatile? An empirical exploration of idiosyncratic risk, *Journal of Finance* **56**, 1–43.

Carlson, M., Fisher, A., and Giammarino, R. (2006) Corporate investment and asset price dynamics: Implications for SEO event studies and long-run performance, *Journal of Finance* **61**, 1009–1034.
Carlson, M., Fisher, A., and Giammarino, R. (2010) SEO risk dynamics, *Review of Financial Studies* **23**, 4026–4077.
Chen, J., Hong, H., and Stein, J. C. (2002) Breadth of ownership and stock returns, *Journal of Financial Economics* **66**, 171–205.
Cochrane, J. H. (2005) *Asset Pricing*. Princeton University Press, Princeton, New Jersey.
Cooper, M., Gulen, H., and Schill, H. (2008) Asset growth and the cross-section of stock returns, *Journal of Finance* **63**, 1609–1651.
DeLong, B., Shleifer, A., Summers, L., and Waldmann, R. (1990) Noise trader risk in financial markets, *Journal of Political Economy* **98**, 703–738.
Diether, K., Malloy, C., and Scherbina, A. (2002) Differences of opinion and the cross section of stock returns, *Journal of Finance* **57**, 2113–2141.
Dittmar, A. K. and Thakor, A. (2007) Why do firms issue equity? *Journal of Finance* **62**, 1–54.
Fama, E. F. and French, K. R. (1993) Common risk factors in the returns of stocks and bonds, *Journal of Financial Economics* **33**, 3–56.
Fama, E. F. and French, K. R. (2005) Financing decisions: Who issues stock? *Journal of Financial Economics* **76**, 549–582.
Fama, E. F. and French, K. R. (2008) Dissecting anomalies, *Journal of Finance* **63**, 1653–1678.
Fama, E. F. and MacBeth, J. (1973) Risk, return, and equilibrium, *Journal of Political Economy* **81**, 607–636.
Frazzini, A. and Lamont, O. (2008) Dumb money: Mutual fund flows and the cross-section of stock returns, *Journal of Financial Economics* **88**, 299–322.
Greenwood, R. and Hanson, S. (2012) Share issuance and factor timing, *Journal of Finance,* forthcoming.
Grullon, G. and Michaely, R. (2004) The information content of share repurchase programs, *Journal of Finance* **59**, 651–681.
Jenter, D. (2005) Market timing and managerial portfolio decisions, *Journal of Finance* **60**, 1903–1949.
Jenter, D., Lewellen, K., and Warner, J. (2011) Security issue timing: What do managers know, and when do they know it? *Journal of Finance* **66**, 413–443.
Kaplan, S. N. and Zingales, L. (1997) Do investment-cash flow sensitivities provide useful measures of financing constraints? *Quarterly Journal of Economics* **112**, 169–215.
Kayhan, A. and Titman, S. (2007) Firms' histories and their capital structures, *Journal of Financial Economics* **83**, 1–32.
Korajczyk, R., Lucas, D., and McDonald, R. (1992) Equity issues with time-varying asymmetric information, *Journal of Financial and Quantitative Analysis* **27**, 397–417.
Kumar, A. (2009) Hard-to-value stocks, behavioral biases, and informed trading, *Journal of Financial and Quantitative Analysis* **44**, 1375–1401.
Li, E., Livdan, D., and Zhang, L. (2009) Anomalies, *Review of Financial Studies* **22**, 4301–4334.
Loughran, T. and Ritter, J. R. (1995) The new issues puzzle, *Journal of Finance* **50**, 23–51.
McLean, R. D., Pontiff, J., and Watanabe, A. (2009) Share issuance and cross-sectional returns: International evidence, *Journal of Financial Economics* **94**, 1–17.
Myers, S. S. and Majluf, N. (1984) Corporate financing and investment decisions when firms have information that investors do not have, *Journal of Financial Economics* **13**, 187–221.
Ofek, E. and Yermack, D. (2000) Taking stock: Equity-based compensation and the evolution of managerial ownership, *Journal of Finance* **55**, 1367–1384.

Pástor, L., Taylor, L., and Veronesi, P. (2009) Entrepreneurial learning, the IPO decision, and the post-IPO drop in firm profitability, *Review of Financial Studies* **22**, 3005–3046.
Pástor, L. and Veronesi, P. (2005) Rational IPO waves, *Journal of Finance* **60**, 1713–1757.
Peyer, U. and Vermaelen, T. (2009) The nature and persistence of buyback anomalies, *Review of Financial Studies* **22**, 1693–1745.
Pontiff, J. (2006) Costly arbitrage and the myth of idiosyncratic risk, *Journal of Accounting and Economics* **42**, 35–52.
Pontiff, J. and Woodgate, A. (2008) Share issuance and cross-sectional returns, *Journal of Finance* **63**, 921–945.
Ritter, J. R. (2003) Investment banking and securities issuance, in: G.M. Constantinides, M. Harris, and R. M. Stulz (eds.) *Handbook of the Economics of Finance*. Vol. 1A, Chapter 5, Elsevier, Amsterdam, pp. 255–306.
Shiller, R. J. (1981) Do stock prices move too much to be justified by subsequent changes in dividends? *American Economic Review* **71**, 421–436.
Shleifer, A. and Vishny, R. (1997) The limits of arbitrage, *Journal of Finance* **52**, 35–55.
Shleifer, A. and Vishny, R. (2003) Stock market driven acquisitions, *Journal of Financial Economics* **70**, 295–311.
Vuolteenaho, T. (2002) What drives firm-level returns? *Journal of Finance* **57**, 233–264.
Wurgler, J. and Zhuravskaya, E. (2002) Does arbitrage flatten demand curves for stocks? *Journal of Business* **75**, 583–608.