On Black's Leverage Effect in Firms With No Leverage

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Abstract

One of the most enduring empirical regularities in equity markets is the inverse relationship between stock prices and volatility. Also known as the "leverage effect", this relationship was first documented by Black (1976), who attributed it to the effects of financial or operating leverage. This paper documents that firms which had no debt (and thus no financial leverage) from January 1973 to December 2017 exhibit Black's leverage effect. Moreover, it finds that the leverage effect of firms in this sample is not driven by operating leverage. On the contrary, in this sample the leverage effect is stronger for firms with low operating leverage as compared to those with high operating leverage. Interestingly, the firms with no debt from the lowest quintile of operating leverage exhibit the leverage effect that is on par with or stronger than that of debt-financed firms.

Keywords: Leverage Effect; Return/Volatility Relationship; Asymmetric Volatility; Debt Financing; Zero Leverage

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1 Introduction

One of the most enduring empirical regularities of equity markets is the fact that stock-return volatility rises after price declines, with larger declines inducing greater volatility spikes. In a seminal paper, Black (1976) provides a compelling explanation for this phenomenon in terms of the firm's financial leverage: a negative return implies a drop in the value of the firm's equity, increasing its leverage which, in turn, leads to higher equity-return volatility. Black further argues that the inverse return/volatility relationship may arise even if the firm has almost no debt because of the presence of so-called operating leverage: because of fixed costs, when income falls it does so by less than expenses, hence firm's equity value falls and its volatility increases. Black's explanations have been so tightly coupled with the empirical regularity that the inverse relation between equity returns and volatility is now commonly known as the "leverage effect".

This effect, and the leverage-based explanation, have been empirically confirmed by a number of studies since Black (1976), e.g., Christie (1982), Cheung and Ng (1992), and Duffee (1995). These studies focus on typical firms (all firms in their respective time frames). They use linear regressions of returns on subsequent changes in volatility for individual stocks and stock portfolios to argue that these relationships become stronger as the firms' debt-to-equity ratios increase. Daouk and Ng (2011) also use a large sample of U.S. firms. By carefully unlevering the levered firms, they show that almost all of the inverse relationship between returns and volatility at the firm level can be explained by financial leverage and, to a smaller extent, operating leverage. In a theoretical model, Aydemir, Gallmeyer, and Hollifield (2006) show that in the economy which is consistent with the assumptions in Black (1976) and Christie (1982) (their benchmark model), the leverage effect hypothesis holds at the firm level, although not at the market level.

However, a growing literature has called into question the validity of the leverage-based explanation. For example, Figlewski and Wang (2000) document several anomalies associated with it, including the fact that the inverse relation becomes much weaker when positive returns reduce leverage. Hens and Steude (2009) find evidence of the "leverage effect" in the data generated by students whom they asked to trade artificial securities with each other using an electronic trading system with no leverage. LeBaron (2014) develops a relatively

simple, computational agent-based model which is successful in replicating several long range empirical features for aggregate stock returns, including the leverage effect. Finally, Kogan (2004) develops a production economy model which implies that market-to-book ratio or q, rather than financial leverage, might lead to the leverage effect.

The debate is far from settled and this paper adds to this literature by testing for Black's leverage explanation using a novel estimation approach: Rather than focusing on typical firms, we consider the extreme case of all-equity-financed firms, i.e., a sample firms that have no debt (and thus no financial leverage) in their capital structures. Using the linear regression specifications considered by prior studies, we check for the presence of an inverse relationship between returns and the subsequent volatility changes in this sample.

We find that all-equity-financed firms from January 1973 to December 2017 exhibit Black's leverage effect. Moreover, we find that the leverage effect of all-equity-financed firms is not driven by operating leverage. On the contrary, among the all-equity-financed firms, the leverage effect is stronger for firms with the low operating leverage as compared to those with high operating leverage. Interestingly, the all-equity-financed firms from the lowest quintile of operating leverage exhibit the leverage effect that is on par with or stronger than that of debt-financed firms.

In Section 2 we provide a review of the literature in which the stock-return/volatility relationship is documented, focusing on a few key regression-based studies that we replicate using the sample of all-equity-financed firms described in Section 3. In Section 4 we describe our empirical strategy, and present results in Section 5. We conclude in Section 6 with a discussion of some possible interpretations of our findings.

2   Literature Review

Black (1976) is widely credited as the originator of the leverage-effect literature. In this pioneering paper, Black uses daily data from 1964 to 1975 of a sample of 30 stocks (mostly Dow Jones Industrials) to study the relationship between volatility changes and returns in individual stocks and the portfolio of those stocks. For each stock, Black constructs 21-day summed returns, and estimates volatility over these intervals with the square root of the sum of squared returns. The portfolio-level equivalents of these estimates, which he calls the

"summed market return" and the "market volatility estimate", are obtained by averaging the summed returns and the volatility estimates, respectively, across the sample of stocks. He then defines the "volatility change" as the difference between the volatility estimate of the current and the previous period, divided by the volatility estimate of the previous period, and regresses the volatility change at time $t+1$ on the summed return at time t. His results suggest a strong inverse relationship between the two: a 1% summed-return decline implies a more than 1% volatility increase.

Black (1976) proposes two possible explanations for this relationship. The first explanation, which he terms the "direct causation" effect, refers to the causal relation from stock returns to volatility changes. A drop in the value of the firm's equity will cause a negative return on its stock and will increase the leverage of the stock (i.e., its debt/equity ratio), and this rise in the debt/equity ratio will lead to a rise in the volatility of the stock. A similar effect may arise even if the firm has almost no debt because of the presence of so-called "operating leverage" (fixed costs that cannot be eliminated, at least in the short run, hence when expected revenues fall, profit margins decline as well). The second explanation, which Black (1976) calls the "reverse causation" effect, refers to the causal relationship from volatility changes to stock returns. Changes in tastes and technology lead to an increase in the uncertainty about the payoffs from investments. Because of the increase in expected future volatility, stock prices must fall, so that the expected return from the stock rises to induce investors to continue to hold the stock.

Using a sample of 379 stocks from 1962 to 1978, Christie (1982) estimates the following linear relationship between changes in volatility from one quarter to the next and the return over the first quarter for each stock:

$$\ln(\frac{\sigma_t}{\sigma_{t-1}}) \;=\; \beta_0 \;+\; \theta_S r_{t-1} \;+\; u_t \tag{1}$$

where σ_{t-1} and r_{t-1} are the volatility estimate and return of the stock over quarter $t-1$. He finds the cross-sectional mean elasticity to be -0.23, consistent with the leverage effect, and then derives testable implications of various volatility models and efficient estimation procedures to investigate the implications of risky debt and interest-rate changes on this relationship. He finds significant positive association between equity volatility and financial

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leverage, but the strength of this association declines with increasing leverage. Christie finds that, contrary to the predictions stemming from the contingent claims literature, the riskless interest rate and financial leverage jointly have a substantial positive impact on the volatility of equity. Finally, he tests the elasticity hypothesis, which says that the observed negative elasticity of equity volatility with respect to the value of equity is, in large measure, attributable to financial leverage. For this purpose he uses the constant elasticity of variance (CEV) model for equity prices, according to which $\sigma_S = \lambda S^\theta$, and estimates the linear regression:

$$\ln(\sigma_{S,t}) \;\; = \;\; \ln(\lambda) \; + \; \theta \ln(S_t) \; + \; u_t \tag{2}$$

where $\sigma_{S,t}$ is the volatility estimated over quarter t, and S_t is the stock price at the beginning of that quarter. He performs two separate tests of the hypothesis that θ_S is a function of financial leverage—one based on leverage quartiles and the other on sub-periods—and finds evidence in support of this hypothesis from both.

Cheung and Ng (1992) examine the inverse relation between future stock volatility and current stock prices using daily returns of 252 NYSE-AMEX stocks with no missing returns from 1962 to 1989, under the assumption of an exponential GARCH model for stock prices (to control for heteroskedasticity and possible serial correlation in their returns). In this model, the conditional variance equation has the logarithm of the lagged stock price on the right-hand side, hence the corresponding coefficient θ is a measure of the leverage effect. Applying the Spearman rank correlation test, the authors find a strong positive correlation between θ and firm size, and explain this pattern by arguing that the smaller the firm, the higher the debt/equity ratio. Their sub-sample analysis shows that the strength of this relationship changes over time. In particular, conditional variances of stock returns on average have become less sensitive to changes in stock prices over time, which, the authors suggest, may be due to an increase in the firms' liquidity over the sample period.

Duffee (1995) provides a new interpretation for the negative relationship between current stock returns and changes in future stock return volatility at the firm level by arguing that it is mainly due to a positive *contemporaneous* relationship between returns and volatility. In addition to the usual test of leverage effect based on lagged returns, Duffee estimates the

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following two contemporaneous regressions:

$$\ln(\sigma_t) \;=\; \alpha_1 \;+\; \lambda_1 r_t \;+\; \epsilon_{t,1} \tag{3}$$

$$\ln(\sigma_{t+1}) \;=\; \alpha_2 \;+\; \lambda_2 r_t \;+\; \epsilon_{t+1,2} \tag{4}$$

and observes that the usual lagged stock-return coefficient is simply the difference $\lambda_0 \equiv \lambda_2 - \lambda_1$. Using data for 2,500 firms traded on the AMEX or NYSE from 1977 to 1991 (not necessarily continuously for the entire sample),[1] Duffee finds that for a typical firm, λ_1 is strongly positive, λ_2 is positive at the daily frequency and negative at the monthly frequency, and that regardless of the sign of λ_2, it is the case that $\lambda_1 > \lambda_2$, implying that $\lambda_0 < 0$. Duffee then tests the theory behind the leverage effect, according to which highly leveraged firms should have a stronger negative relation between stock returns and volatility than less highly leveraged firms. Prior to his study, researchers have documented that the inverse relation between period t stock returns and changes in the stock return volatility from period t to period $t+1$ is stronger for firms with larger debt/equity ratios (e.g., Christie, 1982 and Cheung and Ng, 1992), and that this relation is stronger for smaller firms (Cheung and Ng, 1992). Using the Spearman rank correlations between the individual-firm regression coefficients (λ_0, λ_1, and λ_2) and debt/equity ratios and market capitalizations, Duffee obtains the following three findings: First, the negative relation between λ_0 and the debt/equity ratio found by Christie (1982) and Cheung and Ng (1992) is confirmed only with monthly data for the subset of continuously traded firms. When a larger sample of firms without survivorship bias is used, the correlation between λ_0 and the debt/equity ratio turns positive. Second, highly leveraged firms exhibit stronger negative relations between stock returns and volatility than less highly leveraged firms (the rank correlations between λ_1 and the debt/equity ratio, and λ_2 and the debt/equity ratio, are both negative). And third, because the leverage effect theory has no implications for the strength of the contemporaneous relation between stock returns and volatility, Duffee argues that there is some reason other than the leverage

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[1]It is worth noting that, unlike Black (1976), Christie (1982), and Cheung and Ng (1992) who include only firms that were continuously traded throughout their sample periods, Duffee's (1995) sample is broader, including both continuously traded firms and those that exit the sample, which greatly reduces survivorship bias. He finds that continuously traded firms are, on average, much larger and have lower debt/equity ratios than the typical firm.

effect that is causing at least part of the correlation between firm debt/equity ratios and the regression coefficients, and determining the negative correlation between the firm debt/equity ratio and λ_1. Furthermore, in accordance with Cheung and Ng (1992), he finds that λ_0 is positively correlated with size, at both monthly and daily frequencies, for all firms as well as the sub-sample of continuously traded firms.

Other explanations for the inverse relation between stock volatility and lagged returns have been proposed, each developing into its own strand of literature. The most prominent of these strands is the time-varying risk premia literature, according to which an increase in return volatility implies an increase in the future required expected return of the stock, hence a decline in the current stock price. In addition, due to the persistent nature of volatility (large realizations of either good or bad news increase both current and future volatility), a feedback loop is created: the increased current volatility raises expected future volatility and, therefore, expected future returns, causing stock prices to fall now. The time-varying risk premia explanation, also known as the volatility feedback effect, has been considered by Pindyck (1984), French, Schwert, and Stambaugh (1987), and Campbell and Hentschel (1992), typically using aggregate market returns within a GARCH framework.

Yet another explanation for the inverse relation between volatility and lagged returns, first proposed by Schwert (1989) involves the apparent asymmetry in the volatility of the macroeconomic variables. Empirical evidence suggests that real variables are more volatile in recessions than expansions, hence, if a recession is expected but not yet realized, i.e., GDP growth is forecasted to be lower in the future, stock prices will fall immediately, followed by higher stock-return volatility when the recession is realized.

Disentangling these effects has proved to be a challenging task. For example, using the data for the portfolios of Nikkei 225 stocks and a conditional CAPM model with a GARCH-in-mean parametrization, Bekaert and Wu (2000) reject the leverage model and find support for the volatility feedback explanation. In contrast, examining the relationship between volatility and past and future returns using the S&P 500 futures high-frequency data, Bollerslev, Litvinova, and Tauchen (2006) find that the correlations between absolute high-frequency returns and current and past high-frequency returns are significantly negative for several days, lending support to the leverage explanation, whereas the reverse cross-correlations are negligible, which is inconsistent with the volatility feedback story.

3 Data

Our sample consists of daily stock returns from the University of Chicago's Center for Research in Security Prices, quarterly fundamental data from the CRSP/COMPUSTAT Merged Database (Fundamentals Quarterly), and annual accounting data from COMPUSTAT Fundamentals Annual. We select only those stocks with zero total debt for all quarters from December 1972 to December 2017, where total debt is defined as the sum of total long-term debt, debt in current liabilities (short-term debt), and total preferred stock.[2] Furthermore, in keeping with Black (1976), Christie (1982), and Duffie (1995), we use a 21-day interval to estimate volatilities and returns, and we impose a minimum of 40 daily observations for each regression. These filters yields 275 firms, which comprise our all-equity-financed (AE) sample.

We also construct a complementary sample of firms with positive levels of total debt in their capital structure in every quarter from December 1972 to December 2017. This yields a considerably larger sample of debt-financed (DF) firms. From this universe, we select a smaller subset of 275 firms to match the size distribution and the equity duration of the AE sample.[3] The rationale for matching the size distributions of the two samples is to control for size effects, since we learn from the prior literature that they may matter for the results. For example, Cheung and Ng (1992) show that the leverage effect is much stronger for small stocks. Similarly, Aydemir, Gallmeyer and Hollifield (2006) show that leverage contributes more to the dynamics of stock return volatility for a small firm. The rationale for matching the samples by duration is Chen's (2011) finding that the expected life duration of a stock affects both its returns and the subsequent change in volatility, and we do not want this effect to be stronger in one sample than in the other.

Finally, for each of the two samples (AE and DF), we obtain daily returns from the CRSP

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[2]We first eliminate observations for which any of the long-term debt, current liabilities, or preferred stock is missing. Note that our definition of total debt differs slightly from Christie's (1982), in which short-term debt is measured by the accounting variable "current liabilities" (Compustat mnemonic LCT). This variable is comprised of four components: accounts payable (AP), current liabilities – other – total (LCO), debt in current liabilities (DLC), and income taxes payable (TXP). Since our filter is intended to separate firms with and without debt in their capital structures, we use DLC as our measure of short-term debt.

[3]Specifically, we first sort the AE firms into size quintiles using the average market capitalization of each firm. For each AE size quintile, we take all the DF firms that would fall in it (again, there will be more such DF firms than the corresponding AE firms). Finally, for each AE firm, we select the DF firm from the corresponding size quintile that is closest to it in equity duration.

Daily Database.

4 Empirical Strategy

We test for the leverage effect using linear regression models where the dependent and independent variables of the regression are those proposed by Black (1976), Christie (1982), and Duffee (1995); using all three specifications serves as a robustness check on our results. To obtain the dependent and independent variables used in the regression equations, we first split the daily stock-returns data for each firm or for the portfolios of firms into non-overlapping periods of a certain length, and compute the volatility and total returns over those periods. Then, for each firm or portfolio, we regress the change in volatility between the current period and the previous period on the total return over the previous period, and the change in volatility between the current period and two periods ago on the return in the previous period. The latter regression has the advantage of no data in common to both sides of the regression equation at the same time, which, as Black (1976, p. 181) observes, reduces the chance that the coefficient estimates are biased by errors in the volatility estimates. More formally, we estimate the following eight specifications—each a variation of the same linear regression model—where period $t-1$ returns are related to changes in volatility between periods t and $t-1$ in the first four specifications, and to the changes in volatility between periods t and $t-2$ in the four remaining specifications:

1. `BlackLag1` is given by $\frac{\sigma_t - \sigma_{t-1}}{\sigma_{t-1}} = \alpha + \lambda r_{t-1} + \epsilon_t$, where σ_t is the square root of the sum the squared daily simple returns over period t multiplied by the ratio of 252 to the number of days in period t, and r_t is the sum of daily simple returns over that period.

2. `LogBlackLag1` is given by $\ln(\frac{\sigma_t}{\sigma_{t-1}}) = \alpha + \lambda r_{t-1} + \epsilon_t$, where σ_t and r_t are the same as in `BlackLag1`.

3. `ChristieLag1` is given by $\ln(\frac{\sigma_t}{\sigma_{t-1}}) = \alpha + \lambda r_{t-1} + \epsilon_t$, where σ_t is the square root of the sum of squared daily simple returns over the period, and r_t is the sum of daily log-returns over that period.

4. `DuffeeLag1` is given by $\sigma_t - \sigma_{t-1} = \alpha + \lambda r_{t-1} + \epsilon_t$, where σ_t is the square root of the

sum of squared daily log-returns multiplied by the ratio of 252 to the number of days in period t, and r_t is the sum of daily log-returns over that period.

5. `BlackLag2` is given by $\frac{\sigma_t - \sigma_{t-2}}{\sigma_{t-1}} = \alpha + \lambda r_{t-1} + \epsilon_t$, where σ_t and r_t are the same as in `BlackLag1`.

6. `LogBlackLag2` is given by $\ln(\frac{\sigma_t}{\sigma_{t-2}}) = \alpha + \lambda r_{t-1} + \epsilon_t$, where σ_t and r_t are the same as in `BlackLag1`.

7. `ChristieLag2` is given by $\ln(\frac{\sigma_t}{\sigma_{t-2}}) = \alpha + \lambda r_{t-1} + \epsilon_t$, where σ_t and r_t are the same as in `ChristieLag1`.

8. `DuffeeLag2` is given by $\sigma_t - \sigma_{t-2} = \alpha + \lambda r_{t-1} + \epsilon_t$, where σ_t and r_t are the same as in `DuffeeLag1`.

5 Results

We start by comparing the main characteristics of firms in the two samples to ensure there are no major discrepancies that could be driving the results. We next present results of the leverage effect regressions for the two samples. Finally, we study the strength of the leverage effect for different quintiles of operating leverage in the AE sample.

5.1 Summary Statistics

Table 1 presents summary statistics of the AE and DF samples of firms. This table shows that the distributions of the firms' average market capitalization and equity duration are virtually indistinguishable for the two samples. For example, the mean, median, and standard deviation across firms of the firms' average lifetime market capitalization, measured in billions of dollars, are 0.49, 0.15, and 0.92 in the AE sample. The corresponding values in the DF sample are 0.49, 0.14, and 0.93. The maximum value of average lifetime market capitalization in the DF sample —5.85—is somewhat smaller but still comparable to its AE counterpart of 6.75. Similarly, the mean, median, maximum, and standard deviation across firms of the firms' equity duration, measured in days, are 1966, 1397, 11352, and 1524 in the AE sample. The corresponding values in the DF sample are 1965, 1397, 11352, and 1522.

Although we did not match firms on based on their start date, the average difference in start dates is only 3 years between the two samples.

Dataset	Min	Median	Mean	Max	Std	20%	40%	60%	80%
Summary Statistics of All-Equity Financed (AE) and Debt Financed (DF) Datasets									
Average Market Capitalization ($ billion)									
AE	0.00	0.15	0.49	6.75	0.92	0.04	0.09	0.20	0.61
DF	0.00	0.14	0.49	5.85	0.93	0.04	0.09	0.19	0.60
Equity Duration (days)									
AE	886	1397	1966	11352	1524	1013	1260	1649	2655
DF	886	1397	1965	11352	1522	1013	1261	1649	2656
Start Year									
AE	1973	2002	2001	2014	10	1993	1998	2005	2012
DF	1973	1996	1998	2014	10	1991	1995	1999	2008

Table 1: Distributional summary statistics (market capitalization, equity duration, and start dates) of firms in AE and DF samples. The DF sample is constructed to match both the size distribution and equity duration of the AE sample.

5.2   Financial Leverage

To test whether the leverage effect is due to firms' financial leverage, i.e. the presence of debt in its capital structure, we estimate each of the above regression models on the AE and DF samples from January 2, 1973 to December 31, 2017. As mentioned before, in keeping with Black (1976), Christie (1982), and Duffie (1995), we use a 21-day interval to estimate volatilities and returns, and we impose a minimum of 40 daily observations for each regression.

In Table 2 we report the distributional summary statistics of the individual-firm regression estimates and goodness-of-fit statistics from the AE and DF datasets. For example, according to the top-left panel of Table 2, corresponding to the `BlackLag1` regression specification, the average across 275 firms in the AE dataset of the firm-by-firm "leverage" coefficients λ is -0.49, which is comparable to the average λ of -0.65 for the 275 firms of its DF counterpart. The corresponding median λ's are -0.47 and -0.59 for the AE and DF samples respectively. The average t-statistics are relatively low—-1.12 and -1.49 for the AE and DF datasets, respectively—a finding consistent with Christie (1982), who obtains an average t-statistic of -1.01. The adjusted R^2 statistic tends to be small, ranging across specifications from 1.4% to 5.9% on average, which is also consistent with Christie (1982), who obtains the average

Dataset	Sample Size	Statistic	Min	Median	Mean	Max	Std	Min	Median	Mean	Max	Std
			BlackLag1					BlackLag2				
All-Equity Financed	275	α	0.02	0.13	0.15	0.67	0.09	-0.03	0.15	0.16	0.59	0.10
			(0.34)	(1.78)	(1.90)	(4.76)	(0.71)	(-0.63)	(1.80)	(1.90)	(5.38)	(0.87)
		λ	-2.85	-0.47	-0.49	0.89	0.52	-4.71	-0.38	-0.41	4.17	0.87
			(-4.00)	(-1.02)	(-1.12)	(1.28)	(1.05)	(-5.45)	(-0.88)	(-0.87)	(3.84)	(1.28)
		Adj. R^2	-2.6%	0.1%	1.4%	19.7%	3.7%	-2.6%	0.2%	1.4%	18.1%	3.5%
Debt Financed	275	α	0.04	0.14	0.15	0.49	0.07	-0.02	0.15	0.17	0.54	0.09
			(0.74)	(1.90)	(2.02)	(5.14)	(0.71)	(-0.38)	(1.98)	(2.07)	(4.94)	(0.76)
		λ	-3.51	-0.59	-0.65	0.94	0.60	-4.94	-0.62	-0.69	2.80	0.87
			(-4.72)	(-1.41)	(-1.49)	(1.05)	(1.10)	(-5.00)	(-1.37)	(-1.36)	(3.82)	(1.30)
		Adj. R^2	-2.5%	1.2%	2.8%	34.7%	5.1%	-2.5%	1.2%	3.1%	30.4%	5.5%
			LogBlackLag1					LogBlackLag2				
All-Equity Financed	275	α	-0.08	0.00	0.00	0.12	0.03	-0.14	0.00	-0.01	0.11	0.04
			(-1.13)	(0.00)	(0.05)	(2.24)	(0.44)	(-1.86)	(-0.06)	(-0.09)	(2.30)	(0.52)
		λ	-3.06	-0.51	-0.57	0.76	0.63	-2.44	-0.34	-0.36	2.63	0.62
			(-7.60)	(-1.61)	(-1.64)	(2.27)	(1.59)	(-5.12)	(-1.08)	(-0.99)	(4.18)	(1.32)
		Adj. R^2	-2.6%	2.0%	4.7%	44.3%	7.7%	-2.6%	0.6%	1.8%	20.6%	4.2%
Debt Financed	275	α	-0.06	0.01	0.01	0.11	0.02	-0.11	0.01	0.01	0.11	0.04
			(-0.77)	(0.19)	(0.23)	(1.69)	(0.41)	(-1.79)	(0.11)	(0.14)	(1.56)	(0.51)
		λ	-3.82	-0.60	-0.71	1.22	0.71	-3.11	-0.47	-0.55	1.78	0.66
			(-6.42)	(-1.95)	(-2.03)	(1.55)	(1.57)	(-4.70)	(-1.49)	(-1.43)	(2.53)	(1.27)
		Adj. R^2	-2.6%	3.4%	5.9%	45.6%	7.9%	-2.6%	1.3%	3.1%	31.4%	5.2%
			ChristieLag1					ChristieLag2				
All-Equity Financed	275	α	-0.09	-0.01	-0.01	0.10	0.03	-0.14	-0.01	-0.01	0.09	0.04
			(-1.33)	(-0.14)	(-0.14)	(0.85)	(0.37)	(-1.81)	(-0.14)	(-0.21)	(1.16)	(0.49)
		λ	-2.85	-0.35	-0.42	0.94	0.63	-2.42	-0.36	-0.37	2.70	0.62
			(-5.44)	(-1.04)	(-1.08)	(3.65)	(1.47)	(-5.05)	(-1.09)	(-1.02)	(4.16)	(1.31)
		Adj. R^2	-2.6%	0.9%	2.7%	32.6%	5.7%	-2.5%	0.5%	1.9%	23.3%	4.2%
Debt Financed	275	α	-0.08	0.00	0.00	0.07	0.02	-0.14	0.00	0.00	0.08	0.03
			(-0.88)	(-0.03)	(-0.02)	(0.93)	(0.33)	(-1.89)	(-0.07)	(-0.06)	(1.10)	(0.44)
		λ	-3.71	-0.44	-0.54	1.39	0.70	-2.99	-0.50	-0.56	1.78	0.65
			(-5.64)	(-1.39)	(-1.45)	(1.91)	(1.47)	(-4.69)	(-1.51)	(-1.48)	(2.58)	(1.28)
		Adj. R^2	-2.5%	1.4%	3.5%	33.3%	6.1%	-2.5%	1.7%	3.3%	26.0%	5.4%
			DuffeeLag1					DuffeeLag2				
All-Equity Financed	275	α	-0.07	0.00	0.00	0.11	0.02	-0.08	0.00	0.00	0.13	0.02
			(-0.86)	(-0.09)	(-0.05)	(1.06)	(0.33)	(-1.59)	(-0.09)	(-0.12)	(1.34)	(0.41)
		λ	-1.63	-0.13	-0.09	2.43	0.51	-1.98	-0.22	-0.21	1.10	0.38
			(-5.17)	(-0.57)	(-0.46)	(6.94)	(1.99)	(-5.89)	(-1.00)	(-0.98)	(4.31)	(1.50)
		Adj. R^2	-2.5%	1.5%	3.4%	38.5%	6.3%	-2.6%	0.5%	2.2%	43.3%	5.3%
Debt Financed	275	α	-0.08	0.00	0.01	0.18	0.03	-0.13	0.00	0.00	0.12	0.03
			(-1.16)	(0.00)	(0.07)	(1.33)	(0.36)	(-1.38)	(-0.02)	(0.02)	(1.50)	(0.43)
		λ	-1.44	-0.20	-0.18	1.69	0.46	-1.94	-0.30	-0.37	0.68	0.40
			(-6.65)	(-1.04)	(-1.00)	(4.11)	(1.94)	(-7.37)	(-1.37)	(-1.59)	(2.77)	(1.61)
		Adj. R^2	-2.6%	1.5%	4.0%	34.5%	6.6%	-2.6%	1.4%	4.2%	53.7%	7.4%

Table 2: Summary statistics across all firms in the all-equity-financed (AE) and debt-financed (DF) datasets of the firm-level estimated regression coefficients, their associated t-statistics (reported in parentheses), and the adjusted R^2 goodness-of-fit statistic. Regressions are estimated firm by firm.

adjusted R^2 of 1%.

Similar results are observed in two out of three remaining left-hand-side panels of Table 2, where we regress the change in volatility between the current period and the previous period on the return in the previous period according to the various regressions specifications under consideration. Namely, the average λ's are -0.57 (AE) vs. -0.71 (DF) in `LogBlackLag1` and -0.42 (AE) vs. -0.54 (DF) in `ChristieLag1`. The final left-hand-side specification, `DuffeeLag1`, exhibits the largest λ's for both samples. Specifically, the average λ is -0.09 in the AE sample, which is twice as large as its -0.18 counterpart in the DF sample. However, such a large average λ in the AE sample seems to be driven by a very large maximum λ of 2.43 in that sample. Indeed, the median λ's are closer in magnitude: -0.13 (AE) vs. -0.20 (DF).

For the right-hand-side panels of Table 2, where we regress the change in volatility between the current period and two periods ago on the return in the previous period,[4] there is more of a gap between average λ's of the two datasets, however the median λ's are still comparable: -0.38 (AE) vs. -0.62 (DF) for `BlackLag2`, -0.34 (AE) vs. -0.47 (DF) for `LogBlackLag2`, -0.36 (AE) vs. -0.50 (DF) for `ChristieLag2`, and -0.22 (AE) vs. -0.30 (DF) for `DuffeeLag2`.

These results show that AE firms capture a significant portion of the leverage effect of DF firms. Specifically, considering average λ's, across all specifications, the leverage effect in the AE sample captures over 50 percent of that in the DF sample (i.e., the two samples' average λ's are within at least 50 percent of each other). For 5 out of 8 specifications, it captures over 65 percent. Considering median λ's, the corresponding values are over 60 percent across all specifications, and over 70 percent for 6 out of 8 specifications.

In Table 3 we separate firms into size quintiles based on each firm's average lifetime market capitalization and compute the means and medians of the firm-level leverage coefficients for each quintile. This table reveals that in the AE sample, the average leverage coefficient is at least twice as small for the smallest quintile (Q1) compared to the largest quintile (Q5) when the regressor is defined as the change in volatility between the current period and the previous period: -0.82 (Q1) vs. -0.39 (Q5) for `BlackLag1`, -0.95 (Q1) vs. -0.47 (Q5) for

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[4]Recall Black's (1976) motivation for this procedure was to mitigate the volatility estimation errors by not allowing any data in common to the dependent and independent variables at the same time.

Summary Statistics of Firm-Level Leverage Coefficients by Market Cap Quintile
Samples Matched by Market Capitalization and Equity Duration

Dataset	Market Cap Quintile	Leverage Coefficients (λ)								Average Mkt Cap ($ billion)
		BlackLag1	BlackLag2	LogBlackLag1	LogBlackLag2	ChristieLag1	ChristieLag2	DuffeeLag1	DuffeeLag2	
						Means				
	1	-0.82	-0.35	-0.95	-0.32	-0.78	-0.35	-0.38	-0.30	0.02
	2	-0.51	-0.28	-0.60	-0.27	-0.46	-0.27	-0.12	-0.14	0.06
AE	3	-0.38	-0.38	-0.48	-0.36	-0.34	-0.36	-0.03	-0.17	0.15
	4	-0.33	-0.47	-0.36	-0.39	-0.20	-0.39	0.05	-0.21	0.35
	5	-0.39	-0.58	-0.47	-0.47	-0.34	-0.48	0.01	-0.24	1.87
	1	-0.72	-0.55	-0.79	-0.39	-0.62	-0.44	-0.41	-0.47	0.02
	2	-0.63	-0.64	-0.73	-0.53	-0.56	-0.55	-0.19	-0.39	0.06
DF	3	-0.79	-0.49	-0.74	-0.37	-0.58	-0.39	-0.15	-0.25	0.14
	4	-0.56	-0.64	-0.69	-0.53	-0.54	-0.53	-0.10	-0.28	0.37
	5	-0.53	-1.11	-0.57	-0.94	-0.42	-0.91	-0.07	-0.45	1.88
						Medians				
	1	-0.63	-0.35	-0.71	-0.36	-0.62	-0.45	-0.36	-0.34	0.03
	2	-0.50	-0.30	-0.60	-0.22	-0.48	-0.22	-0.24	-0.15	0.07
AE	3	-0.41	-0.37	-0.42	-0.37	-0.31	-0.38	-0.11	-0.20	0.15
	4	-0.39	-0.33	-0.31	-0.30	-0.13	-0.32	-0.02	-0.17	0.32
	5	-0.35	-0.53	-0.42	-0.39	-0.25	-0.40	-0.05	-0.24	1.30
	1	-0.65	-0.55	-0.64	-0.39	-0.48	-0.41	-0.44	-0.40	0.02
	2	-0.55	-0.62	-0.62	-0.47	-0.48	-0.44	-0.28	-0.35	0.06
DF	3	-0.61	-0.39	-0.62	-0.30	-0.47	-0.40	-0.19	-0.21	0.14
	4	-0.47	-0.55	-0.56	-0.49	-0.45	-0.50	-0.12	-0.27	0.34
	5	-0.44	-0.90	-0.44	-0.71	-0.31	-0.74	-0.06	-0.45	1.43

Table 3: Summary statistics across firms of firm-level leverage coefficients by for subsamples of all-equity-financed (AE) and debt-financed (DF) datasets corresponding to market capitalization quintiles. The quintiles are based on each firm's average lifetime market capitalization.

LogBlackLag1, -0.78 (Q1) vs. -0.34 (Q5) for ChristieLag1, and -0.38 (Q1) vs. 0.01 (Q5) for DuffeeLag1. In the DF sample, the average coefficients also increase from Q1 to Q5 for those same regression specifications, however the difference in much less pronounced. For the remaining regression specifications, the story is reversed. Now the average coefficients are smaller for Q5 than for Q1, and much more so in the DF sample. Specifically, in the DF sample we have: -0.55 (Q1) vs. -1.11 (Q5) for BlackLag2, -0.39 (Q1) vs. -0.94 (Q5) for LogBlackLag2, and -0.44 (Q1) vs. -0.91 (Q5) for ChristieLag2. The corresponding difference in the AE sample is much less pronounced. We draw two main conclusions from these observations. Fist, the pattern of increasing or decreasing leverage effect across size quintiles can depend dramatically on the regression specification considered. Second, for a given specification the pattern is a lot more pronounced for one sample vs. another (e.g., for ChristieLag2 the average Q5 coefficient is over two times smaller than its Q1 counterpart in the DF sample, and only 36 percent smaller in the AE sample). This implies that drawing conclusions from regressions using value-weighted portfolios of AE and DF firms may be misleading, hence in our portfolio-level analysis we focus on equal-weighted portfolios.

Regression Statistics for Equal-Weighted Portfolios of All-Equity-Financed (AE) and Debt-Financed (DF) Firms

		BlackLag1	BlackLag2	LogBlackLag1	LogBlackLag2	ChristieLag1	ChristieLag2	DuffeeLag1	DuffeeLag2
All-Equity Financed	α	0.08	0.11	0.01	0.02	0.01	0.02	0.00	0.00
		(4.34)	(5.38)	(0.71)	(1.27)	(0.62)	(1.17)	(0.71)	(1.47)
	λ	-0.73	-1.64	-0.66	-1.32	-0.62	-1.32	-0.13	-0.31
		(-2.88)	(-5.64)	(-2.95)	(-5.41)	(-2.78)	(-5.41)	(-3.21)	(-6.75)
	Adj. R^2	1.3%	5.4%	1.4%	5.0%	1.2%	5.0%	1.7%	7.7%
Debt Financed	α	0.08	0.11	0.01	0.02	0.01	0.02	0.00	0.00
		(4.31)	(5.23)	(0.71)	(1.33)	(0.59)	(1.20)	(0.50)	(1.48)
	λ	-0.93	-2.05	-0.75	-1.53	-0.70	-1.52	-0.12	-0.36
		(-3.58)	(-6.36)	(-3.37)	(-6.21)	(-3.16)	(-6.21)	(-2.63)	(-7.38)
	Adj. R^2	2.2%	6.8%	1.9%	6.5%	1.6%	6.5%	1.1%	9.1%

Table 4: Estimated regression coefficients, their associated t-statistics (reported in parentheses), and the adjusted R^2 goodness-of-fit statistic for the equal-weighted portfolio of all firms in the all-equity-financed (AE) and debt-financed (DF) datasets.

Table 4 presents results from running leverage effect regressions on the equal-weighted

portfolios of firms in the AE and DF samples.[5] It reveals that the estimated λ for the equal-weighted portfolio of AE firms is close to that of the equal-weighted portfolio of DF firms, for each of the eight regression specifications considered: -0.73 (AE) vs. -0.93 (DF) for `BlackLag1`, -1.64 (AE) vs. -2.05 (DF) for `BlackLag2`, -0.66 (AE) vs. -0.75 (DF) for `LogBlackLag1`, -1.32 (AE) vs. -1.53 (DF) for `LogBlackLag2`, -0.62 (AE) vs. -0.70 (DF) for `ChristieLag1`, -1.32 (AE) vs. -1.52 (DF) for `ChristieLag2`, -0.13 (AE) vs. -0.12 (DF) for `DuffeeLag1`, and -0.31 (AE) vs. -0.36 (DF) for `DuffeeLag2`. Again we see that a significant portion of the leverage effect in DF sample is captured by AE firms. Specifically, the leverage effect in the AE sample is at least 78 percent as strong as that in the DF sample across all regression specifications considered, and over 85 percent as strong for 6 out of 8 specifications.

Estimation errors aside,[6] we conclude that the inverse relationship between a firm's stock return and the resulting change in volatility is present in the AE sample, where it cannot be attributed of the firm's financial leverage.

5.3   Operating Leverage

In this section we study whether the leverage effect observed in all-equity-financed sample of firms is driven by operating leverage, as suggested by Black (1976). Recall that the idea behind the operating leverage explanation for the leverage effect is as follows: because of fixed costs, when income falls it does so by less than expenses, hence firm's equity value falls and its volatility increases. We follow the literature and define operating leverage as the ratio of operating costs to book assets.[7] Operating costs is computed as the sum of Costs of Goods Sold (COGS) and Selling, General and Administrative Expenses (XSGA) items from the COMPUSTAT Fundamentals annual database. Costs of Goods Sold (COGS) item represents all costs directly allocated by the company to production, such as material, labor and overhead. Selling, General and Administrative Expenses (XSGA) item represents all

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[5]The equal-weighted portfolio return, $R_{p,t}$, is computed as $R_{p,t} \equiv \sum_{i=1}^{N} R_{i,t}/N$, where $R_{i,t}$ is the total return (including dividends) of firm i at time t, and where N is the number of firms that exist at the end of time $t-1$.

[6]Recall that coefficient estimates are biased by errors in the volatility estimates, especially when dependent and independent variables are based on the same data at the same time, as is the case here.

[7]See, for example, Novy-Marx (2011) and Garcia-Feijoo and Jorgensen (2010).

commercial expenses of operation (i.e., expenses not directly related to product production) incurred in the regular course of business pertaining to the securing of operating income. Book assets is measured by the AT (Total Assets) item, which represents the total assets of a company at a point in time. When we combine the annual accounting data with the daily stock returns data, we make sure that the accounting data was available at the time the stock return was observed. Namely, the accounting data for the fiscal year ending in calendar year t-1 is considered to be available as of June of year t. We compute the operating leverage quintiles for the all-equity financed (AE) sample, and sort firms from that sample into those quintiles based on the average operating leverage over their lifetime.

Regressions Statistics for 55 AE Firms from the First Quintile of Operating Leverage (OL)
OL is Defined as Operating Costs to Book Assets

Statistic	Min	Median	Mean	Max	Std	Min	Median	Mean	Max	Std
	BlackLag1					BlackLag2				
α	0.03	0.12	0.14	0.56	0.09	-0.03	0.14	0.17	0.46	0.12
	(0.65)	(1.96)	(2.07)	(4.76)	(0.91)	(-0.63)	(2.17)	(2.14)	(5.38)	(1.23)
λ	-2.85	-0.50	-0.61	0.55	0.74	-4.71	-0.55	-0.67	4.17	1.46
	(-2.69)	(-0.95)	(-0.96)	(1.00)	(0.93)	(-5.45)	(-1.27)	(-1.04)	(3.84)	(1.58)
Adj. R^2	-2.3%	0.0%	0.7%	7.7%	2.4%	-2.2%	0.9%	2.2%	17.3%	4.4%
	LogBlackLag1					LogBlackLag2				
α	-0.05	0.01	0.01	0.12	0.03	-0.12	0.00	0.00	0.10	0.04
	(-0.84)	(0.13)	(0.12)	(1.00)	(0.39)	(-1.86)	(0.10)	(-0.02)	(0.97)	(0.57)
λ	-3.06	-0.49	-0.66	0.70	0.84	-2.44	-0.48	-0.46	2.63	0.95
	(-4.28)	(-1.25)	(-1.28)	(2.07)	(1.40)	(-5.12)	(-1.17)	(-1.07)	(4.18)	(1.50)
Adj. R^2	-2.1%	0.8%	2.6%	20.1%	4.5%	-2.5%	0.7%	2.0%	15.6%	3.8%
	ChristieLag1					ChristieLag2				
α	-0.06	0.00	0.00	0.10	0.02	-0.12	0.00	-0.01	0.06	0.03
	(-1.00)	(0.06)	(0.02)	(0.85)	(0.37)	(-1.81)	(-0.02)	(-0.11)	(0.69)	(0.53)
λ	-2.85	-0.33	-0.51	0.93	0.86	-2.42	-0.48	-0.46	2.70	0.95
	(-4.01)	(-0.88)	(-0.88)	(3.09)	(1.45)	(-5.05)	(-1.19)	(-1.10)	(4.16)	(1.50)
Adj. R^2	-2.3%	0.0%	1.7%	16.7%	3.7%	-2.5%	0.8%	2.1%	23.3%	4.4%
	DuffeeLag1					DuffeeLag2				
α	-0.03	0.00	0.00	0.06	0.01	-0.08	0.00	0.00	0.03	0.02
	(-0.64)	(0.06)	(0.04)	(0.81)	(0.36)	(-1.59)	(-0.00)	(-0.13)	(0.55)	(0.46)
λ	-1.19	-0.14	-0.09	2.10	0.49	-1.98	-0.25	-0.27	1.10	0.47
	(-5.06)	(-0.75)	(-0.50)	(6.94)	(2.26)	(-5.89)	(-1.46)	(-1.29)	(3.88)	(1.76)
Adj. R^2	-2.3%	1.0%	3.0%	33.5%	5.8%	-2.5%	1.6%	3.3%	43.3%	7.0%

Table 5: Summary statistics across firms from the first (lowest) quintile of operating leverage (defined as operating costs divided by book assets) in the all-equity-financed (AE) datasets of the firm-level estimated regression coefficients, their associated t-statistics (reported in parentheses), and the adjusted R^2 goodness-of-fit statistic.

In Tables 5–9 we report summary statistics of firm-level regressions for each operating

Statistic	Min	Median	Mean	Max	Std	Min	Median	Mean	Max	Std
	BlackLag1					BlackLag2				
α	0.02	0.13	0.15	0.67	0.10	-0.01	0.15	0.15	0.46	0.09
	(0.34)	(1.70)	(1.89)	(3.88)	(0.81)	(-0.13)	(1.71)	(1.89)	(4.91)	(0.96)
λ	-1.34	-0.41	-0.39	0.38	0.41	-2.52	-0.27	-0.38	1.23	0.68
	(-4.00)	(-0.87)	(-1.14)	(0.89)	(1.21)	(-4.22)	(-0.73)	(-0.93)	(1.82)	(1.28)
Adj. R^2	-2.6%	-0.2%	1.6%	18.7%	4.3%	-2.6%	0.0%	1.5%	18.1%	4.2%
	LogBlackLag1					LogBlackLag2				
α	-0.08	-0.01	0.00	0.08	0.03	-0.14	-0.01	-0.01	0.05	0.04
	(-1.13)	(-0.10)	(-0.05)	(1.05)	(0.41)	(-1.79)	(-0.13)	(-0.19)	(0.86)	(0.52)
λ	-2.02	-0.41	-0.49	0.63	0.50	-2.21	-0.28	-0.35	0.78	0.51
	(-5.15)	(-1.35)	(-1.62)	(2.02)	(1.58)	(-4.25)	(-0.97)	(-1.04)	(2.28)	(1.33)
Adj. R^2	-2.6%	1.0%	4.3%	28.3%	7.5%	-2.6%	0.6%	1.9%	16.4%	4.4%
	ChristieLag1					ChristieLag2				
α	-0.09	-0.01	-0.02	0.04	0.03	-0.14	-0.02	-0.02	0.06	0.04
	(-1.19)	(-0.25)	(-0.24)	(0.53)	(0.36)	(-1.79)	(-0.33)	(-0.32)	(0.80)	(0.52)
λ	-1.72	-0.27	-0.33	0.68	0.48	-2.13	-0.28	-0.36	0.94	0.51
	(-4.42)	(-0.80)	(-1.00)	(3.65)	(1.53)	(-4.23)	(-0.99)	(-1.07)	(2.34)	(1.35)
Adj. R^2	-2.6%	0.2%	2.6%	22.5%	5.9%	-2.5%	0.7%	2.1%	14.9%	4.4%
	DuffeeLag1					DuffeeLag2				
α	-0.06	0.00	0.00	0.11	0.02	-0.08	-0.01	-0.01	0.07	0.02
	(-0.71)	(-0.15)	(-0.11)	(0.76)	(0.35)	(-1.18)	(-0.20)	(-0.21)	(1.32)	(0.46)
λ	-0.96	-0.05	-0.03	2.43	0.55	-0.94	-0.22	-0.20	0.99	0.38
	(-4.31)	(-0.21)	(-0.24)	(5.57)	(2.01)	(-4.81)	(-1.04)	(-0.98)	(4.31)	(1.61)
Adj. R^2	-2.2%	1.2%	3.1%	38.5%	6.9%	-2.6%	0.5%	2.7%	31.1%	6.0%

Table 6: Summary statistics across firms from the second quintile of operating leverage (defined as operating costs divided by book assets) in the all-equity-financed (AE) datasets of the firm-level estimated regression coefficients, their associated t-statistics (reported in parentheses), and the adjusted R^2 goodness-of-fit statistic.

Leverage Regressions for 55 AE Firms from the Third Quintile of Operating Leverage (OL)
OL is Defined as Operating Costs to Book Assets

Statistic	Min	Median	Mean	Max	Std	Min	Median	Mean	Max	Std
			BlackLag1					BlackLag2		
α	0.07	0.13	0.15	0.62	0.09	0.05	0.14	0.16	0.59	0.10
	(1.14)	(1.72)	(1.88)	(3.29)	(0.56)	(0.98)	(1.68)	(1.83)	(3.98)	(0.62)
λ	-1.61	-0.48	-0.49	0.41	0.43	-1.44	-0.36	-0.27	1.90	0.62
	(-3.37)	(-1.30)	(-1.26)	(0.77)	(0.98)	(-4.00)	(-0.78)	(-0.78)	(1.81)	(1.22)
Adj. R^2	-2.5%	0.7%	1.8%	12.9%	3.7%	-2.4%	0.1%	1.0%	10.6%	2.8%
			LogBlackLag1					LogBlackLag2		
α	-0.05	-0.01	0.00	0.09	0.03	-0.10	-0.01	-0.01	0.11	0.04
	(-0.70)	(-0.08)	(0.04)	(2.24)	(0.48)	(-1.05)	(-0.15)	(-0.10)	(2.30)	(0.53)
λ	-2.30	-0.48	-0.55	0.74	0.55	-1.53	-0.26	-0.29	1.18	0.49
	(-5.02)	(-1.66)	(-1.70)	(2.27)	(1.48)	(-3.95)	(-0.88)	(-0.91)	(1.79)	(1.26)
Adj. R^2	-2.4%	1.9%	5.0%	33.5%	7.7%	-2.4%	0.3%	1.5%	16.9%	4.0%
			ChristieLag1					ChristieLag2		
α	-0.08	-0.01	-0.01	0.04	0.02	-0.10	-0.01	-0.01	0.08	0.03
	(-0.91)	(-0.21)	(-0.20)	(0.51)	(0.28)	(-0.97)	(-0.24)	(-0.23)	(0.60)	(0.37)
λ	-2.24	-0.32	-0.42	0.87	0.56	-1.42	-0.30	-0.30	1.19	0.50
	(-4.53)	(-1.15)	(-1.16)	(2.91)	(1.35)	(-4.66)	(-0.93)	(-0.95)	(1.72)	(1.29)
Adj. R^2	-2.2%	1.1%	2.8%	26.7%	6.0%	-2.3%	0.1%	1.5%	16.0%	4.1%
			DuffeeLag1					DuffeeLag2		
α	-0.07	0.00	0.00	0.05	0.01	-0.03	-0.01	0.00	0.10	0.02
	(-0.66)	(-0.14)	(-0.13)	(0.61)	(0.24)	(-0.91)	(-0.12)	(-0.13)	(0.73)	(0.31)
λ	-1.49	-0.14	-0.13	1.13	0.48	-1.91	-0.18	-0.22	0.73	0.39
	(-3.55)	(-0.68)	(-0.53)	(3.89)	(1.75)	(-5.78)	(-0.99)	(-0.97)	(2.21)	(1.49)
Adj. R^2	-2.4%	1.6%	3.0%	20.0%	5.5%	-2.4%	0.5%	1.7%	22.6%	4.4%

Table 7: Summary statistics across firms from the third quintile of operating leverage (defined as operating costs divided by book assets) in the all-equity-financed (AE) datasets of the firm-level estimated regression coefficients, their associated t-statistics (reported in parentheses), and the adjusted R^2 goodness-of-fit statistic.

Leverage Regressions for 55 AE Firms from the Fourth Quintile of Operating Leverage (OL)
OL is Defined as Operating Costs to Book Assets

Statistic	Min	Median	Mean	Max	Std	Min	Median	Mean	Max	Std
	BlackLag1					BlackLag2				
α	0.03	0.15	0.17	0.39	0.09	0.01	0.15	0.17	0.42	0.08
	(0.80)	(1.78)	(1.86)	(3.43)	(0.60)	(0.22)	(1.79)	(1.85)	(3.37)	(0.65)
λ	-2.22	-0.45	-0.41	0.89	0.55	-2.40	-0.37	-0.40	0.86	0.63
	(-3.41)	(-1.10)	(-1.04)	(1.28)	(1.15)	(-4.03)	(-0.84)	(-0.83)	(1.79)	(1.24)
Adj. R^2	-2.3%	0.5%	1.3%	12.6%	3.3%	-2.4%	0.9%	1.6%	12.2%	3.2%
	LogBlackLag1					LogBlackLag2				
α	-0.08	0.00	0.00	0.09	0.03	-0.11	-0.01	-0.01	0.08	0.04
	(-0.98)	(0.05)	(0.05)	(1.34)	(0.46)	(-1.51)	(-0.10)	(-0.08)	(1.07)	(0.48)
λ	-2.57	-0.58	-0.54	0.76	0.67	-1.59	-0.37	-0.38	0.61	0.51
	(-7.60)	(-1.93)	(-1.88)	(1.60)	(2.06)	(-4.01)	(-1.12)	(-1.08)	(1.46)	(1.39)
Adj. R^2	-2.4%	3.7%	6.4%	44.3%	9.8%	-2.3%	1.0%	2.5%	19.7%	4.6%
	ChristieLag1					ChristieLag2				
α	-0.09	-0.01	-0.01	0.06	0.03	-0.13	-0.01	-0.02	0.09	0.04
	(-1.33)	(-0.17)	(-0.16)	(0.72)	(0.39)	(-1.78)	(-0.11)	(-0.20)	(1.16)	(0.49)
λ	-2.44	-0.41	-0.39	0.94	0.66	-1.72	-0.39	-0.40	0.60	0.51
	(-5.44)	(-1.47)	(-1.18)	(2.25)	(1.72)	(-3.91)	(-1.16)	(-1.06)	(1.49)	(1.30)
Adj. R^2	-2.5%	2.7%	3.7%	32.6%	6.5%	-2.2%	0.9%	2.2%	14.9%	4.0%
	DuffeeLag1					DuffeeLag2				
α	-0.04	0.00	0.00	0.11	0.03	-0.06	0.00	0.00	0.13	0.03
	(-0.86)	(-0.04)	(-0.01)	(1.06)	(0.35)	(-1.48)	(-0.07)	(-0.06)	(1.34)	(0.42)
λ	-1.63	-0.24	-0.07	1.78	0.62	-1.11	-0.17	-0.19	0.53	0.34
	(-5.17)	(-1.16)	(-0.41)	(5.19)	(2.26)	(-5.61)	(-0.87)	(-0.83)	(2.06)	(1.42)
Adj. R^2	-2.5%	2.2%	5.0%	38.2%	7.8%	-2.4%	0.3%	2.0%	21.7%	4.7%

Table 8: Summary statistics across firms from the fourth quintile of operating leverage (defined as operating costs divided by book assets) in the all-equity-financed (AE) datasets of the firm-level estimated regression coefficients, their associated t-statistics (reported in parentheses), and the adjusted R^2 goodness-of-fit statistic.

Regression Statistics for 55 AE Firms from the Fifth Quintile of Operating Leverage (OL)
OL is Defined as Operating Costs to Book Assets

Statistic	Min	Median	Mean	Max	Std	Min	Median	Mean	Max	Std
	BlackLag1					BlackLag2				
α	0.04	0.14	0.16	0.39	0.06	0.00	0.15	0.16	0.52	0.09
	(0.67)	(1.74)	(1.79)	(3.19)	(0.58)	(0.04)	(1.77)	(1.76)	(3.07)	(0.68)
λ	-1.49	-0.51	-0.52	0.29	0.36	-2.06	-0.40	-0.33	1.63	0.59
	(-3.87)	(-0.98)	(-1.19)	(0.57)	(0.96)	(-2.36)	(-0.77)	(-0.76)	(1.50)	(1.01)
Adj. R^2	-2.2%	-0.1%	1.8%	19.7%	4.5%	-2.6%	-0.2%	0.7%	7.8%	2.6%
	LogBlackLag1					LogBlackLag2				
α	-0.05	0.00	0.00	0.08	0.03	-0.11	0.00	-0.01	0.06	0.04
	(-0.77)	(0.00)	(0.08)	(1.46)	(0.45)	(-1.41)	(-0.01)	(-0.06)	(0.97)	(0.50)
λ	-2.24	-0.53	-0.62	0.55	0.52	-1.94	-0.27	-0.34	1.37	0.54
	(-6.27)	(-1.62)	(-1.71)	(1.55)	(1.36)	(-3.51)	(-0.59)	(-0.87)	(1.88)	(1.14)
Adj. R^2	-2.4%	2.1%	5.0%	40.2%	7.6%	-2.5%	0.4%	1.4%	20.6%	4.2%
	ChristieLag1					ChristieLag2				
α	-0.08	-0.01	-0.01	0.06	0.03	-0.12	-0.01	-0.01	0.06	0.04
	(-0.87)	(-0.12)	(-0.14)	(0.85)	(0.38)	(-1.57)	(-0.09)	(-0.17)	(0.89)	(0.51)
λ	-1.98	-0.39	-0.47	0.70	0.52	-1.96	-0.25	-0.34	1.41	0.54
	(-5.13)	(-1.14)	(-1.20)	(2.05)	(1.29)	(-3.09)	(-0.77)	(-0.89)	(2.26)	(1.14)
Adj. R^2	-2.6%	1.0%	2.9%	30.7%	5.8%	-2.5%	0.4%	1.4%	17.6%	3.9%
	DuffeeLag1					DuffeeLag2				
α	-0.04	0.00	0.00	0.03	0.02	-0.04	0.00	0.00	0.08	0.02
	(-0.61)	(-0.06)	(-0.02)	(0.84)	(0.32)	(-1.15)	(-0.05)	(-0.06)	(0.96)	(0.39)
λ	-1.34	-0.17	-0.16	0.76	0.42	-0.95	-0.20	-0.19	0.86	0.31
	(-4.51)	(-0.82)	(-0.65)	(2.64)	(1.62)	(-3.30)	(-0.71)	(-0.81)	(2.65)	(1.17)
Adj. R^2	-2.4%	0.6%	2.7%	25.4%	5.3%	-2.5%	-0.1%	1.2%	19.8%	3.8%

Table 9: Summary statistics across firms from the fifth (highest) quintile of operating leverage (defined as operating costs divided by book assets) in the all-equity-financed (AE) datasets of the firm-level estimated regression coefficients, their associated t-statistics (reported in parentheses), and the adjusted R^2 goodness-of-fit statistic.

leverage quintile, from the first (lowest) to the fifth (highest). If the leverage effect in the AE sample were driven by operating leverage, then we would expect the leverage coefficients for that sample to be more negative in the higher operating leverage quintiles than in the lower ones. However, these tables reveal that in seven out of eight regression specifications λ is more pronounced in the lowest (Q1) than in the highest (Q5) operating leverage quintile: -0.61 (Q1) vs. -0.52 (Q5) for `BlackLag1`, -0.67 (Q1) vs. -0.33 (Q5) for `BlackLag2`, -0.66 (Q1) vs. -0.62 (Q5) for `LogBlackLag1`, -0.46 (Q1) vs. -0.34 (Q5) for `LogBlackLag2`, -0.51 (Q1) vs. -0.47 (Q5) for `ChristieLag1`, -0.46 (Q1) vs. -0.34 (Q5) for `ChristieLag2`, and -0.27 (Q1) vs. -0.19 (Q5) for `DuffeeLag2`. Only for `DuffieLag1` is this relationship reversed: -0.09 (Q1) vs. -0.16 (Q5).

Finally, as Table 10 reveals, for equal-weighted portfolios of firms, the leverage effect is stronger from Q1 than for Q5 for all 8 regression specifications, and at least one-and-a-half times as strong for 7 of them: -1.18 (Q1) vs. -0.76 (Q5) for `BlackLag1`, -1.57 (Q1) vs. -0.53 (Q5) for `BlackLag2`, -1.32 (Q1) vs. -0.74 (Q5) for `LogBlackLag1`, -1.31 (Q1) vs. -0.48 (Q5) for `LogBlackLag2`, -1.20 (Q1) vs. -0.69 (Q5) for `ChristieLag1`, -1.33 (Q1) vs. -0.49 (Q5) for `ChristieLag2`, -0.29 (Q1) vs. -0.25 (Q5) for `DuffeeLag1`, and -0.34 (Q1) vs. -0.19 (Q5) for `DuffeeLag2`.

The above results show that the presence of the leverage effect in AE firms, which again are free from financial leverage, cannot be attributed to operating leverage either, thus ruling out Black's leverage explanation for the leverage effect in this sample.

6 Conclusion

The inverse relationship between equity returns and subsequent volatility changes is one of the most well-established empirical regularities in stock-market data. Traditionally, this relationship is considered to be the result of leverage. This paper documents the leverage effect in firms with no leverage and further shows that in that sample the leverage effect cannot be explained by operating leverage.

Our analysis does not provide a clear-cut alternative to the leverage explanation. By ruling out leverage as the source of the return/volatility relationship, our results may be interpreted as supportive of the time-varying expected return hypothesis of Pindyck (1984),

Regression Statistics for Equal-Weighted Portfolios of AE Firms by OL Quintile
OL is Defined as Operating Costs to Book Assets

	BlackLag1	BlackLag2	LogBlackLag1	LogBlackLag2	ChristieLag1	ChristieLag2	DuffeeLag1	DuffeeLag2
				OL Q1				
α	0.10	0.12	0.02	0.02	0.01	0.01	0.00	0.00
	(4.72)	(5.00)	(0.91)	(0.78)	(0.68)	(0.64)	(0.60)	(0.63)
λ	-1.18	-1.57	-1.32	-1.31	-1.20	-1.33	-0.29	-0.34
	(-3.45)	(-4.04)	(-4.71)	(-4.32)	(-4.24)	(-4.37)	(-3.80)	(-4.35)
Adj. R^2	2.1%	2.9%	3.9%	3.3%	3.2%	3.4%	2.5%	3.3%
				OL Q2				
α	0.09	0.11	0.01	0.01	0.01	0.01	0.00	0.00
	(4.04)	(4.31)	(0.55)	(0.61)	(0.30)	(0.41)	(0.20)	(0.37)
λ	-0.75	-0.99	-0.70	-0.83	-0.59	-0.85	-0.15	-0.29
	(-3.01)	(-3.48)	(-3.47)	(-3.81)	(-2.88)	(-3.88)	(-1.88)	(-3.54)
Adj. R^2	1.8%	2.5%	2.5%	3.0%	1.6%	3.1%	0.6%	2.6%
				OL Q3				
α	0.10	0.12	0.01	0.01	0.00	0.00	0.00	0.00
	(3.80)	(4.05)	(0.34)	(0.29)	(0.18)	(0.18)	(0.20)	(0.20)
λ	-0.59	-0.78	-0.69	-0.62	-0.62	-0.62	-0.19	-0.19
	(-2.21)	(-2.67)	(-3.31)	(-2.83)	(-2.97)	(-2.84)	(-3.06)	(-3.02)
Adj. R^2	0.9%	1.4%	2.3%	1.6%	1.8%	1.7%	1.9%	1.9%
				OL Q4				
α	0.11	0.12	0.02	0.01	0.01	0.00	0.01	0.00
	(4.62)	(4.36)	(1.08)	(0.34)	(0.59)	(0.14)	(0.57)	(0.02)
λ	-0.72	-0.57	-0.87	-0.54	-0.78	-0.58	-0.37	-0.19
	(-4.12)	(-2.70)	(-6.00)	(-3.31)	(-5.15)	(-3.40)	(-4.61)	(-2.17)
Adj. R^2	3.4%	1.4%	7.3%	2.2%	5.4%	2.3%	4.3%	0.8%
				OL Q5				
α	0.12	0.13	0.02	0.01	0.01	0.01	0.01	0.00
	(5.10)	(4.77)	(1.03)	(0.41)	(0.76)	(0.30)	(0.89)	(0.37)
λ	-0.76	-0.53	-0.74	-0.48	-0.69	-0.49	-0.25	-0.19
	(-3.67)	(-2.08)	(-4.24)	(-2.42)	(-3.89)	(-2.45)	(-4.55)	(-2.98)
Adj. R^2	2.3%	0.6%	3.1%	0.9%	2.6%	0.9%	3.6%	1.5%

Table 10: Estimated regression coefficients, their associated t-statistics (reported in parentheses), and the adjusted R^2 goodness-of-fit statistic for the equal-weighted portfolio of firms from the first (lowest) to the fifth (highest) quintile of operating leverage (defined as operating costs divided by book assets), in the all-equity-financed (AE) dataset.

French, Schwert, and Stambaugh (1987), and Campbell and Hentschel (1992). Our findings provide support for the volatility feedback model of Danielsson, Shin, and Zigrand (2009), in which asset-market volatility is endogenously determined in equilibrium by a combination of leverage constraints, feedback effects, and market conditions.

However, our results are also consistent with a behavioral interpretation in which investors' behavior is shaped by their recent experiences, altering their perceptions of risk and, consequently, giving rise to changes in their demand for risky assets. Such biased perceptions of risk have been modeled by Gennaioli and Shleifer (2010), in which individuals make judgments by recalling past experiences and scenarios that are the most representative of the current situation, and combining these experiences with current information. Such judgments will be biased not only because the representative scenarios that come to mind depend on the situation being evaluated, but also because the scenarios that first come to mind tend to be stereotypical ones. In our context, the first memories that come to mind of an investor who has experienced significant financial loss is despair; as a result, emotions take hold, prompting the investor to quickly reverse his positions, rather than continuing with a given investment policy. Since, as documented by Strebulaev and Yang (2013), all-equity-financed firms tend to have higher CEO ownership, smaller and less independent boards, or be family run, all of which may imply less checks and balances, such path-dependent cognitive perception of risk may be especially pronounced in our sample.

The view that our recent experiences can have substantial effects on our future behavior is also backed by Lleras, Kawahara, and Levinthal (2009). In their research, Lleras and his co-authors show that memories of past experiences affect the kinds of information we pay attention to today. In particular, they compare the effects on the attention system of externally-attributed rewards and penalties to the memory-driven effects that arise when subjects repeatedly perform a task, and find that in both cases the attention system is affected in analogous ways. This leads them to conclude that memories are tainted (positively or negatively) by implicit assessments of our past performance.

Additional support for a behavioral interpretation of the leverage effect may be found in the aforementioned experimental evidence of Hens and Steude (2009). Recall that in their study, 24 students were asked to trade artificial securities with each other using an electronic trading system. They found that returns generated by these trades were negatively

correlated with changes in future volatility estimates. Clearly in this experimental context, neither leverage nor time-varying expected returns can explain the inverse return/volatility relationship.

Finally, our finding that among the all-equity-financed firms, the leverage effect is the strongest for firms with the lowest levels of operating leverage also points to the behavioral explanation. The management of these firms seems to be extremely risk averse in not taking leverage of any kind (perhaps because they are ill-equipped to manage it, which again would be consistent with Strebulaev and Yang's (2013) characterization), and yet they cannot avoid the leverage effect.

To distinguish among these competing explanations, further empirical and experimental analysis—with more explicit models of investor behavior and market equilibrium—is required. We hope to pursue these extensions in future research.

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