New evidence on sources of leverage effects in individual stocks

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New Evidence on Sources of Leverage Effects in Individual Stocks

Geoffrey Peter Smith*

Abstract

I test Black’s leverage effect hypothesis on a panel of U.S. stocks from 1997 to 2012. I find that negative stock return innovations increase the future volatility of equity returns by about 36% more than positive ones. There is a strong and positive relation between variation in the size of these leverage effects and variation in the firm’s use of debt. I uncover this relation by applying the Fama/French/Carhart 4-factor asset pricing model in the EGARCH mean equation and by using panel data to control for firm- and time-invariant unobservables via first differences and two-way fixed effects.

Keywords: Leverage effect, EGARCH, volatility, panel data

JEL classification: G12, G17, G19

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1. Introduction

It is well-known that negative stock return innovations increase the future volatility of equity returns more than positive ones.\textsuperscript{1} Black (1976) is widely credited as the first to document this phenomenon and attribute it to financial leverage. According to Black’s leverage effect hypothesis, decreases in the market value of equity trigger automatic increases in the debt-to-equity ratio and in the ensuing volatility of equity returns. Christie (1982) tests this hypothesis and finds that stock return volatility is an increasing function of financial leverage and that this explains why the elasticity of volatility with respect to the value of equity is negative.

The hypotheses tests in Christie (1982) assume that expected stock returns are constant and that stock return volatility is neither autocorrelated nor conditionally heteroskedastic. We now know from the GARCH (generalized autoregressive conditional heteroskedasticity) model of Engle (1982) and Bollerslev (1986) that these assumptions are unrealistic. The GARCH model is unable to capture Black’s leverage effects because the GARCH conditional variance equation does not depend on the sign of the return innovation. To capture this effect, Nelson (1991) develops the EGARCH (exponential GARCH) model, wherein an explicit leverage effect parameter is estimated in order to capture the difference between negative and positive stock return innovations on the future volatility of equity returns. This leverage effect parameter is suitable for testing hypotheses on whether variation in the size of the leverage effect is due to variation in financial leverage.

One of the first to apply the EGARCH to test the leverage effect hypothesis, Koutmos and Saidi (1995) estimate leverage effect parameters on the daily stock returns of the 30 companies in the Dow Jones Industrial Average. Their purpose is to determine whether cross sectional variation in the EGARCH leverage effect parameter is explained by cross sectional

\textsuperscript{1} See, for example, Pagan and Schwert (1990), Bollerslev, Chou, and Kroner (1992), Pagan (1996), and Engle (2004).
variation in the firm’s debt-to-equity ratio. They find that while the stock returns exhibit leverage effects, in the sense that negative stock return innovations increase future volatility by about 2.13 times more than positive innovations do, there is no strong relation between variation in the size of these effects and variation in the firm’s debt-to-equity ratio.

Other studies applying alternative approaches are also inconclusive on whether leverage effects are due to financial leverage. For example, Duffee (1995) finds that the results in Christie (1982), which are based on a sample of very large firms, disappear when a broader set of firms is examined. Bekaert and Wu (2000) apply a general empirical framework based on a multivariate GARCH-in-mean model to conclude that leverage effects are not driven by changes in financial leverage. Daouk and Ng (2011) develop a new unlevering approach and find that financial leverage explains much of the volatility asymmetry at the firm level. Hasanhodzic and Lo (2011) look at all-equity-financed firms and find that leverage effects are just as strong (if not stronger) than firms with financial leverage. Thus there is no consensus on whether leverage effects are due to variation in financial leverage as predicted by Black.

The aim of this study is to provide more conclusive evidence in favor of or against Black’s leverage effect hypothesis. My main innovation is that I apply the practical approach of Koutmos and Saidi (1995) while making several improvements to their econometric method. The biggest improvement is that I control for firm- and time-invariant unobservables by using panel data to estimate first difference and two-way fixed effects regressions. I replace the AR(1) specification used by Koutmos and Saidi in the EGARCH mean equation with the 4-factor asset pricing model of Fama and French (1993) and Carhart (1997). The explanatory variables in my regressions are predetermined and exogenous. In addition to the 30 stocks in the Down Jones
Industrial Average, my sample includes stocks in the Standard & Poor’s 500-stock index (S&P 500 index).

It turns out that these improvements make a difference. I find negative stock return innovations increase the future volatility of equity returns by about 36% more than positive stock return innovations. I find a strong and positive relation between variation in the size of these effects and variation in financial leverage, represented as the ratio of interest expense to total assets, and overall cash flow, represented as the ratio of operating income before depreciation to total assets. I find no relation between the size of the leverage effects and dividends, represented as the ratio of dividends to total assets.

These results are consistent with the predictions of Black’s leverage effect hypothesis and provide more convincing evidence on the sources of leverage effects than previous studies do. Since development of a better understanding of the nature and sources of volatility is vital in areas such as option pricing and risk management, the insights gained by this study have important practical implications as well as important implications for future research.

2. Data and method

If Black’s leverage effect hypothesis is correct, then variation in the size of the EGARCH leverage effect parameter can be explained by variation in financial leverage. In this section, I describe how I estimate the EGARCH parameters and calculate financial leverage for each firm in each year of my sample. For clarity of exposition, the variable names in parentheses below are identical to the variable names on the data sources.

I begin with all of the stocks in the S&P 500 index on July 1, 1996. These stocks are some of the most liquid and most actively traded in the world and thus make a good sample
insofar as illiquidity and nonsynchronous trading effects are unlikely to contaminate the time series of their daily stock returns. The 4-factor asset pricing model of Fama and French (1993) and Carhart (1997), which I use to calculate their expected returns, is also very likely to be a good model for the expected returns on these stocks.

For each of the stocks in this sample, I calculate leverage effects by estimating the EGARCH model of Nelson (1991) on their daily excess stock returns in each year from July 1 of year \( t + 1 \) to June 30 of year \( t + 2 \) (\( t = 1996 \) to 2010). In order to estimate the model, the stocks must have no missing returns data for each year in the sample period. Specifically, let \( RETRF_n \) be the excess stock return for each stock on each day \( n \), calculated as the daily stock return (RET) minus the daily U.S. Treasury bill rate of return (RF) from the Center for Research in Security Prices (CRSP) database (in percent). Then for each stock in each year let:

\[
RETRF_n = a + bMKTRF_n + sSMB_n + hHML_n + mUMD_n + e_n,
\]

where \( MKTRF_n, SMB_n, HML_n, \) and \( UMD_n \) are the day \( n \) returns on the market, size, book-to-market, and momentum risk-factor mimicking portfolios of Fama and French (1993) and Carhart (1997) from CRSP (in percent). The \( a \) is the intercept term and \( b, s, h, \) and \( m \), are the usual risk-factor loadings. The \( e_n \) is a normally distributed mean zero daily stock return innovation.

The daily stock return innovation, \( e_n \), follows an EGARCH process when:

\[
e_n = \sigma_n \epsilon_n, \quad \ln(\sigma_n^2) = \omega + \alpha \epsilon_{n-1} + \gamma [\epsilon_{n-1} - E(\epsilon_{n-1})] + \beta \ln(\sigma_{n-1}^2),
\]

where \( \omega, \alpha, \gamma, \) and \( \beta \) are real constants.
The difference between the effect of negative and positive stock return innovations on future volatility can more easily be seen by rewriting \( g(\epsilon_{n-1}) = \alpha \epsilon_{n-1} + \gamma [|\epsilon_{n-1}| - E(|\epsilon_{n-1}|)] \)
as:

\[
g(\epsilon_{n-1}) = \begin{cases} 
(\alpha + \gamma) \epsilon_{n-1} - \gamma E(|\epsilon_{n-1}|) & \text{if } \epsilon_{n-1} \geq 0; \\
(\alpha - \gamma) \epsilon_{n-1} - \gamma E(|\epsilon_{n-1}|) & \text{if } \epsilon_{n-1} < 0.
\end{cases}
\]

The difference between the effect of negative and positive stock return innovations on future volatility is then given by:

\[
\lambda = \exp^{-4\alpha} - 1,
\]

for a stock return innovation two standard deviations in size. That is, \( \lambda \times 100 \) is the percentage difference between the effect of a size two standard deviation negative stock return innovation and a size two standard deviation positive stock return innovation on future volatility. I refer to the variable \( \lambda_{t+1} \) as the leverage effect for each stock in each year \( t + 1 \) with the expectation that \( \alpha \) is negative in the data.

I estimate the above-described EGARCH model via the method of maximum likelihood for each stock in each year from July 1 of year \( t + 1 \) to June 30 of year \( t + 2 \) to get a cross section and time series of estimates for \( a, b, s, h, m, \omega, \alpha, \gamma, \) and \( \beta \). Convergence of the likelihood function is achieved for all but two firm-years out of 3,750 (99.95% success rate).\(^2\)

To test whether variation in the size of \( \lambda_{t+1} \) is due to variation in financial leverage, I calculate financial leverage as the ratio of interest expense (XINT) to total assets (AT) for each

\(^2\) I estimate the EGARCH parameters using computer software provided by the R Project for Statistical Computing in conjunction with the rugarch package of Ghalanos (2014). The EGARCH parameters are estimated using the “hybrid” strategy solver option in order to maximize the possibility of convergence of the likelihood function.
firm in each fiscal year ending \( t \) from the Compustat database (in percent). I refer to this variable as \( XINT_t \). Using a cash flow based variable to represent financial leverage avoids the well-known errors in variables problem associated with using the book value of debt because the book value of debt is likely to be different from the market value of debt. Thus, my financial leverage variable is not affected by changes in the yield to maturity that occur over time due to changes in risk. In other words, I treat the cash flows to bondholders as fixed rather than assume the market value of debt is fixed.

In addition to \( XINT_t \), I calculate \( DVC_t \) as the ratio of dividends (DVC) to total assets and \( OIBDP_t \) as the ratio of operating income before depreciation (OIBDP) to total assets for each firm in each fiscal year (in percent). I include \( DVC_t \) and \( OIBDP_t \) to control for the market value of equity and the market value of the firm, respectively, since the market value of equity is the discounted present value of the dividends and the market value of the firm is the discounted present value of the before-tax cash flows. My expectation is that there is a negative relation between \( \lambda_{t+1} \) and \( DVC_t \) and \( OIBDP_t \) since a higher debt-to-equity ratio will cushion against the effect of bad news on expected future cash flows and the future volatility of equity returns in accordance with the leverage effect hypothesis.

Data on the leverage effect for each firm in each year, \( \lambda_{t+1} \), is merged with the predetermined exogenous data on \( XINT_t \), \( DVC_t \), and \( OIBDP_t \). From this panel data set, I remove financial firms (SIC codes 6000 to 6999) because the high leverage that is normal for these firms does not have the same meaning as it does for non-financial firms. I also remove utilities (SIC codes 4900 to 4999) because their financing decisions can be subject to regulatory supervision. Next, I remove firms whose common stock does not trade on the NYSE, Amex, or Nasdaq stock exchanges. Lastly, the variables \( XINT_t \), \( DVC_t \), and \( OIBDP_t \) are scaled by total assets and this
creates influential observations when total assets are close to zero. Data errors can also be a problem. To address these issues, I follow Fama and French (1998) and drop the extreme 0.5% of observations in each tail of the distribution for each of these variables. The remaining firms with no missing data form a final balanced panel data set of 1,965 firm-year observations for fiscal years ending 1996 to 2010.

Table 1 reports the cross section and time series of descriptive statistics for the parameters estimated via the EGARCH model described by Equation (1) and Equation (2).

[insert Table 1 about here]

Consistent with the presence of leverage effects, the mean $\alpha$ is -0.022. Inserting this mean $\alpha$ into Equation (4) indicates that negative stock return innovations two standard deviations in size increase the future volatility of equity returns by an average of 24% more than positive stock return innovations do. The median $\alpha$ is -0.033, which indicates that the median percentage difference in effect between negative and positive stock return innovations on future volatility is 36%. In comparison, Koutmos and Saidi (1995) report that negative innovations increase future volatility by about 2.13 times more than positive innovations do for their sample of the 30 stocks in the Dow Jones Industrial Average. The mean and median $b$ are 1.006 and 0.991, which indicates that the sample stocks are about as risky as the average stock in terms of market risk. The mean and median $\beta$ are 0.682 and 0.842, which accounts for the well-known regularity that stock return volatility is highly autocorrelated.
Table 2 reports the cross section and time series of descriptive statistics for the leverage effect, financial leverage, dividend, and operating cash flow variables that I use to test the leverage effect hypothesis.

The mean and media for $\lambda_{t+1}$ are 0.358 and 0.140. The mean and median for $XINT_t$ are 1.539 and 1.415, indicating that the sample firms pay out about 2% of assets each year in interest expense. The mean and median for $DVC_t$ are 2.138 and 1.713, indicating that sample firms also pay out about 2% of assets each year in dividends. The mean and median for $OIBDP_t$ are 16.126 and 15.889, indicating that sample firms earn about 16% of assets each year in operating income before depreciation.

It is with the data summarized in Table 2 that I test Black’s leverage effect hypothesis. If the hypothesis is correct, I expect to find a positive and significant relation between $\lambda_{t+1}$ and $XINT_t$, and a negative and significant relation between $\lambda_{t+1}$ and $DVC_t$ and $OIBDP_t$.

To test for these relations, I estimate regressions of the following form:

$$\lambda_{t+1} = \phi_0 + \phi_1 XINT_t + \phi_2 DVC_t + \phi_3 OIBDP_t + u_{t+1},$$  \hspace{1cm} (5)

where $\phi_0$, $\phi_1$, $\phi_2$, and $\phi_3$ are the constant term and mean effects of financial leverage, dividends, and operating income before depreciation, respectively, on the size of the leverage effect. Firm subscripts that should appear on each of the variables are omitted for readability. The parameter $\phi_1$ will be positive and significant if Black’s leverage effect hypothesis is correct and variation in the size of the leverage effect is explained by variation in financial leverage.
One of the major advantages gained by using panel data to test this hypothesis is the ability to control for firm- and time-invariant effects in the unobservables, $u_{t+1}$. To control for the firm-invariant effects, I estimate Equation (5) on the data in first differences. Since first differencing only controls for the firm-invariant effects, I also estimate two-way fixed effects “within” regressions in which the firm- and time-invariant effects are removed by demeaning the data. A third approach, two-way random effects regressions, is ruled out by applying the Hausman test of Hausman (1978). The Hausman test results show that the fixed effects parameter estimates are consistent and preferred in comparison to the random effects parameter estimates. I also estimate three specifications of Equation (5) to control for correlation in the explanatory variables.

Lastly, I base tests of the significance of the parameters from Equation (5) on heteroskedasticity and cluster robust standard errors calculated via the method of White (1980) and Arellano (1987). I discuss the results from these tests in the following section.

3. Results

Table 3 reports the parameter estimates and standard errors from estimation of Equation (5) via first differences and by estimating two-way fixed effects “within” regressions.\(^3\)

[insert Table 3 about here]

The results of the regressions on the first differenced data support Black’s leverage effect hypothesis. The parameter estimates for $\phi_1$ of 0.332, 0.330, and 0.328 for each of the regression

---

\(^3\) I estimate these regressions using computer software provided by the R Project for Statistical Computing in conjunction with the plm package of Croissant and Millo (2008).
specifications are all significant at the 1% level. Dividends have no effect on the size of the leverage effect, but operating income before depreciation does. The significant parameter estimate for $\phi_3$ of 0.017 contradicts my initial conjecture that higher overall cash flows cushion against the effects of bad news on the future volatility of equity returns. Rather, it appears that the effect of bad news on future volatility increases with operating income possibly due to disappointment by stockholders over unexpectedly poor performance by the firm.

The results of the two-way fixed effects regressions also support Black’s leverage effect hypothesis. The parameter estimates for $\phi_1$ of 0.165, 0.172, and 0.184 for each of the regression specifications are all significant at the 1% level. Once again, dividends have no effect on the size of the leverage effect, but operating income before depreciation does. The significant parameter estimate for $\phi_3$ of 0.011 suggests that stockholders are disappointed by bad news about firms with higher levels of operating income before depreciation.

Overall, my tests uncover strong evidence of a positive and highly significant relation between variation in the size of the EGARCH leverage effect parameter and variation in the ratio of interest expense to total assets. I find an unexpected positive and significant relation between variation in the size of the leverage effect and variation in the ratio of operating income before depreciation to total assets and no relation between the size of the leverage effect and the ratio of dividends to total assets.

4. Conclusion

I find new evidence in favor of Black’s leverage effect hypothesis in a panel of U.S. stocks from 1997 to 2012. I find that negative stock return innovations increase the future volatility of equity returns by about 36% more than positive stock return innovations. I find that
variation in the size of these leverage effects is positively and significantly related to financial leverage. Variation in the size of these leverage effects is positively and significantly related to variation in operating income before depreciation, suggesting that bad news has a larger effect on future volatility for firms with a higher amount of operating cash flow. There is no relation between the size of the leverage effect and the amount of dividends.

Naturally, there are other possible sources of leverage effects that this study does not look into. For example, Avramov, Chordia, and Goyal (2006) suggest that leverage effects are due to differences in trading activity between uniformed and informed investors. Dennis, Mayhew, and Stivers (2006) suggest that leverage effects are caused by systematic market-wide factors rather than aggregated firm-level effects. Nevertheless, this study concludes that Black’s leverage effect hypothesis reasonably explains why negative stock return innovations increase the future volatility of equity returns more than positive stock return innovations.

References


Table 1

**Maximum likelihood estimates for the EGARCH model**

Reported are the descriptive statistics for parameters estimated via the EGARCH model:

\[
\begin{align*}
RETRF_n &= a + bMKTRF_n + sSMB_n + hHML_n + mUMD_n + e_n \\

\ln(\sigma_n^2) &= \omega + \alpha e_{n-1} + \gamma [|e_{n-1}| - E(|e_{n-1}|)] + \beta \ln(\sigma_{n-1}^2).
\end{align*}
\]

\(RETRF_n\) is the daily stock return (RET) minus the daily U.S. Treasury bill rate of return (RF) for each firm on each day \(n\) from CRSP (in percent). \(MKTRF_n, SMB_n, HML_n, \) and \(UMD_n\) are the daily returns on the market, size, book-to-market, and momentum risk-factor-mimicking portfolios from CRSP, respectively (in percent). Parameters are estimated for each firm in each year from July 1 of year \(t+1\) to June 30 of year \(t+2\) \((t = 1996\) to 2010\).

<table>
<thead>
<tr>
<th>a</th>
<th>b</th>
<th>s</th>
<th>h</th>
<th>m</th>
<th>(\omega)</th>
<th>(\alpha)</th>
<th>(\gamma)</th>
<th>(\beta)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>-0.002</td>
<td>1.006</td>
<td>0.071</td>
<td>0.150</td>
<td>-0.065</td>
<td>0.247</td>
<td>-0.022</td>
<td>0.180</td>
</tr>
<tr>
<td>Median</td>
<td>0.004</td>
<td>0.991</td>
<td>0.020</td>
<td>0.116</td>
<td>-0.042</td>
<td>0.075</td>
<td>-0.033</td>
<td>0.164</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>0.119</td>
<td>0.341</td>
<td>0.451</td>
<td>0.756</td>
<td>0.541</td>
<td>0.675</td>
<td>0.167</td>
<td>0.365</td>
</tr>
<tr>
<td>Minimum</td>
<td>-0.909</td>
<td>-0.769</td>
<td>-1.342</td>
<td>-4.007</td>
<td>-4.001</td>
<td>-4.841</td>
<td>-0.576</td>
<td>-0.738</td>
</tr>
<tr>
<td>Maximum</td>
<td>0.582</td>
<td>3.058</td>
<td>2.379</td>
<td>3.561</td>
<td>2.550</td>
<td>6.103</td>
<td>0.596</td>
<td>7.019</td>
</tr>
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Table 2
Descriptive statistics for variables used in the regressions
Reported are descriptive statistics taken over the cross section and time series for variables used to test Black’s leverage effect hypothesis. The $\lambda_{t+1}$ represent leverage effects, i.e., the difference between the effect of negative and positive stock return innovations on the future volatility of equity returns for individual stocks from July 1 of year $t+1$ to June 30 of year $t+2$. $XINT_t$ is interest expense, $DVC_t$ is dividends, and $OIBDP_t$ is operating income before depreciation, all scaled by total assets for each firm in each FYE $t$ ($t = 1996$ to $2010$) (in percent).

<table>
<thead>
<tr>
<th></th>
<th>$\lambda_{t+1}$</th>
<th>$XINT_t$</th>
<th>$DVC_t$</th>
<th>$OIBDP_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean</td>
<td>0.358</td>
<td>1.539</td>
<td>2.138</td>
<td>16.126</td>
</tr>
<tr>
<td>Median</td>
<td>0.140</td>
<td>1.415</td>
<td>1.713</td>
<td>15.889</td>
</tr>
<tr>
<td>Std. Dev.</td>
<td>1.054</td>
<td>0.814</td>
<td>1.763</td>
<td>6.414</td>
</tr>
<tr>
<td>Minimum</td>
<td>-0.908</td>
<td>0.021</td>
<td>0.000</td>
<td>-4.547</td>
</tr>
<tr>
<td>Maximum</td>
<td>9.004</td>
<td>5.150</td>
<td>9.772</td>
<td>37.388</td>
</tr>
</tbody>
</table>
Table 3
Panel data regression results
Reported are parameter estimates from first differences and fixed effects regressions of:

\[
\lambda_{t+1} = \phi_0 + \phi_1 XINT_t + \phi_2 DVC_t + \phi_3 OIBDP_t + u_{t+1}.
\]

The \(\lambda_{t+1}\) represent leverage effects, i.e., the difference between the effect of negative and positive stock return innovations on the future volatility of equity returns for individual stocks from July 1 of year \(t + 1\) to June 30 of year \(t + 2\). \(XINT_t\) is interest expense, \(DVC_t\) is dividends, and \(OIBDP_t\) is operating income before depreciation, all scaled by total assets for each firm in each FYE \(t\) (\(t = 1996\) to \(2010\)) (in percent). Heteroskedasticity and cluster robust standard errors are calculated via the method of White (1980) and Arellano (1987) (in parenthesis). The total number of firm year observations is 1,965.

<table>
<thead>
<tr>
<th>Estimate</th>
<th>First differences</th>
<th>Fixed effects</th>
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<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>(\phi_0)</td>
<td>0.013</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>(\phi_1)</td>
<td>0.332**</td>
<td>0.330**</td>
</tr>
<tr>
<td></td>
<td>(0.128)</td>
<td>(0.128)</td>
</tr>
<tr>
<td>(\phi_2)</td>
<td>0.036</td>
<td>0.008</td>
</tr>
<tr>
<td></td>
<td>(0.062)</td>
<td>(0.063)</td>
</tr>
<tr>
<td>(\phi_3)</td>
<td>0.017*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td></td>
</tr>
<tr>
<td>(F)-stat.</td>
<td>11.957</td>
<td>6.107</td>
</tr>
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</table>

** and * represent significance at the 0.01 and 0.05 levels, respectively.