Stock return volatility, operating performance and stock returns: International evidence on drivers of the 'low volatility' anomaly

Tanuj Dutt [a], Mark Humphery-Jenner [a,b,*]

[a] *Nuvest Capital, Singapore*

[b] *Australian School of Business, University of New South Wales, Sydney, Australia*

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Abstract

This study highlights the link between stock return volatility, operating performance, and stock returns. Prior studies suggest that there is a 'low volatility' anomaly, where firms with a low stock return volatility out-perform firms with a high stock return volatility. This paper confirms that low volatility stocks earn higher returns than high volatility stocks in emerging markets and developed markets outside of North America. We also show that low volatility stocks have higher operating returns and this might explain why low volatility stocks earn higher stock returns. These results provide a partial explanation for the 'low volatility effect' that is independent from the existence of market anomalies or per se inefficiencies that might otherwise drive a low volatility effect. We emphasize the importance of controlling for stock return volatility when analyzing operating performance and stock performance.

JEL classification: G11; G12

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*Corresponding author. Tel.: +61 2 9385 1000.

E-mail addresses: TanujDutt@nuvestcap.com (T. Dutt), m.humpheryjenner@unsw.edu.au (M. Humphery-Jenner)

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1. Introduction

Prior studies have documented that 'low volatility' stocks tend to outperform 'high volatility' stocks, particularly in the US. Thus, this paper tests two issues: (a) whether the 'low volatility anomaly' documented in holds outside of the US, and particularly in emerging markets, and (b) whether a driver of this effect might be the relationship between low volatility returns and operating performance. In so doing, we establish that low volatility indeed leads to stronger operating performance, the low volatility effect exists in both emerging markets and developed markets outside of North America, and strong operating performance might at least partially account for the low volatility effect. These findings are robust to addressing issues of thin trading and transactions costs.

Low volatility investing has become an important issue in portfolio management.[1] Baker, Bradley, and Wurgler (2011) find that, for the US, stocks in the bottom volatility-quintile on average earn higher future returns than do stocks in the other volatility quintiles. Other papers have reported similar results for the US and for developed markets (Ang et al., 2006, 2009; Blitz and van Vliet, 2007).[2] Baker, Bradley, and Wurgler (2011) argue that the low volatility effect arises because sophisticated investors must adhere to a benchmark; and thus, are unable to fully exploit an arbitrage opportunity whereby it might be possible to systematically earn higher returns while assuming lower risk. Supporting this theory, Chan et al (2002) find that mutual

[1] See for example: Blitz and van Vliet (2007); Clarke et al (2006, 2011); Ang et al (2006, 2009); Lee (2011); Pachamanova (2006); Alexander and Barbosa (2007).

[2] Although, we note that the low volatility effect does not have universal support (see Bali et al., 2005; Bali and Cakici, 2008) .

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funds tend to stick towards a broad market benchmark. Subsequently, anomalies, such as the low volatility anomaly, can persist because institutional investors cannot fully exploit the excess returns they could gain from investing in such stocks. Additionally, the evidence that 'style drift' away from such a benchmark tends to harm performance,[3] would further discourage funds from actively seeking to exploit such anomalies.

The 'limits to arbitrage' explanation is a very plausible explanation it need not be the only explanation for the low volatility effect. The 'limits to arbitrage' explanation is particularly strong for US markets. This is because the US SEC requires funds to disclose a relevant benchmark (see Form N-1A). This requirement does not exist in all non-US markets. Further, other markets have a higher proportion of retail investors (following Gao and Lin, 2012; Kuo and Lin, 2012), who would be less constrained to follow a benchmark. While we do believe that benchmarking is important for investors in non-US markets, its effect might be weaker outside of the US. Also, the 'limits to arbitrage' explanation may be less dominant in 'global emerging markets' portfolios where any benchmarking may actually encourage institutional investors to invest in these low volatility stocks that comprise emerging markets benchmarks.[4]

[3] Chan et al (2002) find that poorly performing mutual funds tend to shift styles; Cumming et al (2009) find a negative relationship between style drift and performance in the private equity industry.

[4] The fact that portfolio managers tend not to disclose their portfolio holdings makes it difficult to present direct evidence of this effect. However, Alti et al (2012) highlight that emerging-market portfolio managers are sensitive to information asymmetries, and prefer to invest in companies with better information disclosures (which are typically larger, more stable stocks). Further, to the extent that portfolio managers (partially) disclose their portfolio holdings, there is evidence that some emerging market portfolio managers prefer to invest in large, highly capitalized, companies (see e.g. the investments of Colonial First state (2012); it is also implied in the approach of Schroders (2011), who purport to derive 50% of their value from country selection (i.e. country beta) and have an investible universe of only 700 stocks across 25 countries, implying that they focus on larger, more stable, companies).

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It is ex ante unclear whether limits on arbitrage would produce a low volatility effect in emerging markets. This is for several reasons. First, most commonly followed emerging market equity index benchmarks tend to comprise fewer stocks and tend to comprise the most stable stocks. Thus, investors benchmarked to these indices should be more able to arbitrage-away any potential excess profits that could arise from mispricing of low volatility stocks. Thus, we would postulate that the low volatility anomaly, if it exists within emerging markets, may be weaker or may have a different explanation.

Second, foreign (i.e. US) investors interested in investing in emerging markets might focus on the 'cleanest' exposure to emerging market growth, with the lowest levels of information asymmetry/ information opacity[5] These are typically larger stocks that are less volatile. This focus on large stocks means that investors may be more able to arbitrage-away any low volatility anomaly that exists in emerging markets. Thus, if limits on arbitrage are the only explanation for the low volatility effect, it might again be weaker in emerging markets.

Further, different markets have different laws and different securities exchange regulations.[6] These regulations can influence factors such as stock market liquidity (Cumming et al., 2011c), and the location of trade of cross-listed stock (Halling et al., 2008). This suggests that it is important to verify that the low volatility effect exists in different regulatory environments.

[5] See for example the results documented in: Grinblatt and Keloharju (1999) document a home-language bias in investments. Coval and Moskowitz (1999) find a home bias in US funds. Brennan et al (2005) find that foreign investors have an informational disadvantage.

[6] Myriad papers document differences in securities laws and regulations between markets, and document that these influence the way in which traders behave and influence the efficiency and liquidity of financial markets (e.g. La Porta et al., 1997, 1998; Cumming and Johan, 2008; Djankov et al., 2008; Spamann, 2010; Cumming et al., 2011c; Humphery-Jenner, 2011a, 2012).

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This begs the questions: does the low volatility effect still hold in emerging markets or in markets outside the US, and if so, is there an additional explanation for the presence of the low volatility effect?

One additional possible explanation for the 'low volatility effect' relates to operating performance and investment. Low volatility stocks would likely have strong operating performance as low volatility improves the firm's access to capital. In an efficient market, there should be an association between stock returns and (positive) earnings surprises, but not merely between stock returns and earnings per se (following Core et al., 2006). However, strong operating performance could increase returns for several reasons that we document in Section 3. These include the fact that strong low volatility facilitates access to capital, which can assist long-dated and entrepreneurial projects. Such projects might have distant cash flows, which the market will rationally discount (Martin, 2012). Subsequently, there will be an increase in stock price over time as information about the success of these projects becomes available.

We investigate the two issues: (a) does the low volatility anomaly exist outside of the US, and (b) could it have another explanation, such as higher stock returns reflecting consistently higher operating returns and earnings surprises? Any additional explanation would not be inconsistent with the explanation offered in Baker, Bradley, and Wurgler (2011), instead, there can be multiple consistent and complementary explanations for any low volatility anomaly.

The results allow us to make two key findings. First, we find that the low volatility effect does exist in non-US markets and in emerging markets, and that the low volatility effect may partially

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reflect a firm's strong operating performance.[7] We find that firms in the lowest volatility quintile outperform those in other quintiles both in emerging markets and in developed markets outside of North America. Low volatility stocks also out-perform high volatility stocks in the across the major emerging regions: emerging Asia, Latin America, and EMEA (Europe Middle, East, and Africa). We find evidence largely consistent with a low-volatility effect in non-US/Canadian developed markets. This holds whether we examine value-weighted or equal-weighted portfolios.

Second, we show a significant relationship between low volatility and strong operating performance and that this can account for at least part of the low volatility effect. Part of the out-performance of low volatility stocks relates to operating performance. Specifically, the spread between 'strong' and 'weak' operations companies partially explains the monthly stock return spread between 'stable' and 'volatile' companies.

Further, we find that low volatility firms have significantly higher operating returns in addition to higher stock returns, and that firms with higher operating returns are likely to be in lower volatility quintiles. We also find a statistically significant reduction in the impact of 'volatility' on stock returns after controlling for operating performance.[8] This implies that there is a relationship between strong operating performance and low volatility.

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[7] The results focus on 'absolute volatility' rather than on idiosyncratic volatility. This is for two main reasons: First, the goal is to directly examine the implications of the Baker et al (2011) model. Second, focusing on absolute volatility avoids the need to determine an appropriate market benchmark from which to compute idiosyncratic volatility. This avoids complications that might arise due to the documented home asset bias in investment.

[8] We identify this by examining the impact on the volatility/return relationship after controlling for operating performance in a Fama and French (1993) type framework.

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There are several potential explanations for the relationship between operating performance, volatility, and returns. The results could reflect the possibility that low volatility firms are able to outperform market expectations, thereby generating positive unexpected news. Alternatively, the result may arise where the market expects low volatility stocks to outperform, but the uncertainty associated with this out-performance means that the market does not immediately impound its expectations into prices, causing the market to re-evaluate stock prices over time as information becomes more certain. Additionally, in emerging markets, the result is consistent with the theory of return-persistence in Alti et al (2012). The theory is that if the information environment is poor and investors feel positively about a stock, then investors might interpret subsequent strong operating figures as confirmation of their beliefs. This perceived conformation can cause investors to over-estimate the precision of their information and upwardly value the stock.

We ensure that the results are robust to the main criticism of the low volatility effect: its economic tractability in the presence of transactions costs. Li et al (2012) argue that the low volatility effect is not beneficial after controlling for the presence of low liquidity and high trading costs. Similarly Liang and Wei (2012) show that low liquidity stocks command a risk premium. However, we find that low volatility stocks still earn higher stock returns even after controlling for low liquidity.[9] Indeed, we find that low volatility stocks still earn higher returns even after removing the 10% least liquid stocks from the sample.[10] We also find some evidence that the low volatility effect is weaker for firms who experience operating performance

[9] Specifically in robustness tests, discussed in Section 4.3, we control for a proxy for transactions costs: the proportion of days on which there is a zero return (following Lesmond et al., 1999).
[10] We document this evidence in Section 2, where we present evidence of the long-run out-performance of low volatility stocks in developed and emerging markets.

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improvements/surprises, consistent with the idea that the low volatility effect might merely reflect the information associated with positive earnings surprises.

The structure of this paper is as follows. Section 2 demonstrates that there is a low volatility effect in both developed and emerging markets. The results show that low volatility companies earn higher returns than do high volatility companies. Section 3 explores a possible driver for the low-volatility effect; strong and stable operating performance. The rationale is that companies with strong operating results might be more stable and predictable; and thus, also have lower volatilities. Section 4 concludes.

2. Does the low volatility effect exist internationally?

The first major issue is to test if the low volatility effect exists outside of the US and Canada. This is of general interest from a portfolio construction perspective because it helps to indicate whether a low volatility strategy is effective in multiple markets. However, it is especially important to confirm the existence of a low volatility effect because not all markets will equally exhibit the limits to arbitrage documented in Baker et al (2011). This can be due to different stock exchange rules and regulations. For example US SEC Rules require mutual funds to set a benchmark against which to compare returns (Baker et al., 2011).[11] Such rules do not exist in all markets. Additionally, some markets might feature a higher proportion of retail investors (Ferreira and Matos, 2008), who are less constrained to invest around a benchmark. Further, as

[11] SEC Form N-1A, promulgated under the Securities Exchange Act 1933, requires open end funds to disclose (inter alia) their investment objectives and goals. The form also states that a fund 'may' identify its type (such as a money market fund or a managed fund). Funds must also disclose any benchmark against which the fund's performance is assessed for the purpose of compensation.

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suggested above, benchmarking in emerging markets might encourage funds to invest in low volatility companies; and thus, might enable them to arbitrage-away any mispricing that arises due to a ‘low volatility effect’.

We obtain daily stock price data from Compustat Global over the period 1990 – 2010. For each stock, we calculate the 90 day, 180 day, 250 day, 500 day, and 1000 day moving variance (of stock returns). We report results based on the 500-day moving variance (but ensure that the results are qualitatively robust to the other windows). We classify firms based on the location of the stock exchange as belonging to one of four markets: Emerging Asia,[12] Emerging EMEA,[13] Latin America[14] and Ex-US/Canada Developed.[15] Given that our focus is on whether the low volatility effect exists outside of the US/Canada, we do not include US and Canadian firms in the sample.

We analyze the returns as follows: Split the sample into sub-samples based on the exchange being located in a developed marked, emerging Asia, Emerging EMEA, and Latin America (we also analyze a pooled sample of developed and emerging markets). For each stock on each day we calculate the moving average stock-return variance and turnover over the prior 500 days, and

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[12] Emerging Asia comprises exchanges in India, Indonesia, Malaysia, Pakistan, the Philippines, South Korea, Taiwan, and Thailand. We exclude China from the sample on grounds that there are significant restrictions on foreign investors investing in Chinese-listed companies.

[13] Emerging EMEA comprises the Czech Republic, Egypt, Hungary, Israel, Jordan, Morocco, Poland, Russia, South Africa, Turkey, and Argentina.

[14] Latin America comprises Argentina, Brazil, Chile, Colombia, Mexico, Peru, and Venezuela.

[15] The developed markets are Australia, Austria, Belgium, Bermuda, Britain, Cyprus, Denmark, Finland, France, Germany, Greece, Hong Kong, Ireland, Israel, Italy, Japan, Mauritius, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, and Switzerland.

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we calculate the daily USD market capitalization.[16] Focus on the first day of each month. Exclude all firms whose USD market capitalization is in the bottom 10% of the firm's stock-exchange-country, or whose average turnover is in the bottom 10% of the region (although the results are robust to not imposing such a threshold). Removing low liquidity stocks is important to address the claim that the low volatility effect is mainly driven by low liquidity stocks (Li et al., 2012). Further, removing low liquidity stocks helps to ensure that the results do not merely reflect the low liquidity risk premium documented in Liang and Wei (2012). For the each of the four sub-samples we calculate return-volatility quintiles. We create portfolios for each return-variance quintile. We rebalance the portfolio on the first day of each month. For each day in that month, we then calculate the value weighted average, and equally weighted average, daily return for the portfolio. The value-weightings are based on the firm's contribution to the total USD market capitalization of the portfolio (at the beginning of the month, when the portfolio is formed). We then report what $1 invested in each portfolio would be worth today.

The results show that low volatility portfolios perform better than do high volatility portfolios. Figure 1 contains the results for value weighted portfolios. Figure 2 and Figure 3 contains the results for equally weighted portfolios. Figure 1 and Figure 2 split the sample into developed markets, emerging Asia, emerging Latin America, and emerging Europe. Figure 3 splits the sample into emerging and developed markets. In most cases, firms in the lowest volatility quintiles (quintiles 1 and 2) experience higher stock returns. The high volatility quintiles (especially quintile 5) experience lower stock returns. An exception to this is in developed markets, where quintile 2 has the best performance. This suggests that some level of volatility is

[16] We compute the variance after converting prices to USD. That is, we first convert prices to USD using the contemporaneous exchange rate. Then, we compute the variance of these returns. The results are qualitatively robust to foregoing the conversion to USD.

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desirable. We also note that the shape of the graphs broadly resembles those of the relevant MSCI regional indexes. We observe a dip in market values around the time of the Asian financial crisis.

[Insert Figure 1about here]

[Insert Figure 2 about here]

[Insert Figure 3 about here]

We also report the average yearly returns earned by each quintile-portfolio in each region. Table 1 contains the average yearly returns and Figure 4 plots them. The figures are based on a value-weighted portfolio of stocks that is rebalanced every month. The reported results are the average return between 1995 and 2009. We construct the portfolios as indicated above. The key result is that the average return for the lower quintile portfolios is higher than for the higher quintile portfolios. This holds across all regions. A similar patter exists when we analyze the returns in each month (although we suppress these results for brevity).

[Insert Figure 4 about here]

[Insert Table 1 about here]

The results are robust to the precise composition of the sample. We note that our sample comprises over 90% by market capitalization of the overall investible universe, as proxied by the S&P index universe (excluding the US and Canada). The results are robust to classification; we obtain similar results if we define developed markets as in Ang et al (2009) although our sample

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does not include Canada and the United States.[17] We define the emerging markets as the 35 Dow Jones emerging markets. [18]The results also hold when we just split the sample into developed and non-developed markets. We also ensure that they are robust to restricting the analysis to only the top 2000 stocks by USD market capitalization in the sample. This sub-sample produces results that are consistent with the reported results.

Overall, the results suggest that the low volatility anomaly exists across both global emerging markets and global developed markets. It also exists in the major regional sub-groupings of global emerging markets i.e Emerging Asia, Emerging EMEA and Latin America. The issue is then whether this stronger stock performance relates to a stronger operating performance.

3. Why might strong operating performance sound in higher stock returns and explain the volatility effect?

We next address why the low volatility effect might be related to operating performance. We argue that an additional (but compatible) reason could be that low volatility companies also have strong operating returns. There are several reasons to suspect a relationship between low volatility, operating performance, and returns.

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[17] Ang et al (2009) analyze 23 developed markets (including Canada and the United states). The other countries are Australia, Austria, Belgium, Denmark, Finland, France, Germany, Greece, Hong Kong, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Singapore, Spain, Sweden, Switzerland, and the United Kingdom.

[18] The Dow Jones list of 35 emerging markets comprises: Argentina, Bahrain, Brazil, Bulgaria, Chile, China, Colombia, Czech Republic, Egypt, Estonia, Hungary, India, Indonesia, Jordan, Kuwait, Latvia, Lithuania, Malaysia, Mauritius, Mexico, Morocco, Oman, Peru, Philippines, Poland, Qatar, Romania, Russia, Slovakia, South Africa, Sri Lanka, Taiwan, Thailand, Turkey, and the United Arab Emirates.

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First, consider the case where the high operating returns are unexpected. Here, the firm will experience higher stock returns as the market re-evaluates the price of the stock. As suggested in Core et al (2006), this is the situation that is most likely to result in positive stock returns. Here, the earnings surprise is likely to result in positive returns. Such earnings surprises might be more likely to accrue to low volatility companies because such companies have better access to capital, so will be more able to invest in entrepreneurial companies.

Second, consider the situation where the strong operating performance is not per se a surprise, but is uncertain to arise. Here, we envisage a situation where the market might expect these low volatility companies to perform well (i.e. due to better access to capital), but this strong performance is not guaranteed. Nonetheless, it is still possible that such performance could result in stock price gains for several reasons:

1. Revelation of information over time: Strong operating performance causes traders to re-evaluate the company and bid up the stock price. This is consistent with market efficiency because even if the market expected strong operating performance, there is always some risk of weak operating performance. This uncertainty will make the market's reaction to the expectation of strong earnings more muted (Francis et al., 2007; Bird and Yeung, 2012). The production of strong performance would resolve this uncertainty and induce the market to bid-up the stock.[19] That is, as performance becomes more certain that the firm will actually achieve its (predicted) strong earnings, its price

[19] We note that strong performance could arguably reduce the firm's required rate of return; and thus, reduce stock returns. However, this assumes that stronger operating returns are certain. Instead, there is uncertainty surrounding operating performance; and thus, even if the market expects strong operating returns, the reduction in uncertainty about them could still induce investors to bid-up stock prices and increase returns.

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will drift towards the value implied by those earnings, reflecting a reduction in the risk that the firm will not meet earnings forecasts (consistent with Zhang, 2006).[20]

2. Risky expansion options and information: Strong operating performance enables the company to pursue expansion opportunities. This would increase operating risk without per se increasing short run stock price volatility. Ritter (2003) suggests that it is possible that the increased risk from aggressive expansion can more than off-set the (risk reduction) benefits of having more cash.[21] This effect would be stronger if managers use excess cash flows to engage in agency-motivated investments (as per Jensen, 1986).[22] This effect would also be present in emerging markets, which feature worse governance and more agency conflicts in general (Black et al., 2010), and generally feature lower levels of investor protection (see e.g. La Porta et al., 1997, 1998; Cumming and Johan, 2008; Djankov et al., 2008; Spamann, 2010; Cumming et al., 2011c).[23] These expansion

[20] It is for this reason that there is a well-documented drift-upwards in target share prices after a takeover announcement. In the takeover context, there is uncertainty about the consummation of a takeover, so is uncertainty about whether the target will really obtain the takeover premium. As this uncertainty decreases, the target's price drifts upwards (Schwert, 1996; Cumming and Li, 2011).

[21] The precise quote is "It is…entirely conceivable that lower leverage is more than offset by increased operating risk, if issuing companies embark on aggressive expansion plans with the money raised by an SEO". The quote relates to SEOs but applies mutatis mutandis to general cash flows.

[22] In unreported results, we find evidence that is consistent with the prediction that free cash flows (FCF) can enable managers to act on agency conflicts. First, following Florackis and Ozkan (2009), we examine the impact of FCF on sales growth and find that FCF leads to a reduction in Sales/Assets. Second, using Tobin's Q as a proxy for firm-value, we find that FCF leads to a reduction in Tobin's Q. Of course, some literature shows that riskier expansion can decrease corporate risk if managers optimally perceive expansion as a real option, and optimally exercise that option (Carlson et al., 2006). And, this could potentially induce higher stock returns (Grullon et al., 2012). However, it can often be difficult for managers to optimally value and exercise real options, especially in the context of emerging markets where managers might not always be well trained and/or companies might feature poor corporate governance. Further, even if managers can effectively utilize real options, there is growing evidence that the market tends to penalize investments in such risky projects due, at least in part, to the market often placing especial emphasis on the possibly of 'disastrous' outcomes in long-dated investments (Weitzman, 2009; Martin, 2012).

[23] Shareholder-manager agency conflicts are not the only (or even the most prevalent) conflict in emerging markets, with shareholder-shareholder conflicts, whereby major shareholders might act to the detriment of minor shareholders, being a significant concern (Khanna, 2000; Khanna and Palepu, 2000; Khanna and Yafeh, 2007; Cumming et al., 2011a, 2011b; Masulis et al., 2011; Bhaumik and Selarka, 2012; Liu and Tian, 2012). Nonetheless, the existence of shareholder-shareholder conflicts does not prevent shareholder-manager conflicts from being a significant source of agency costs (following Chen et al., 2011; Cumming et al., 2011b;

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opportunities should lead to an increase in corporate value (albeit an uncertain increase). The uncertainty associated with this increase means that the market will not fully impound the value of these cash flows until they materialize, especial where, as here, there is significant uncertainty as to their attainment (Martin, 2012). This explanation can operate in conjunction with the explanation offered in Baker et al (2011).

3. Return persistence: There is some evidence of return-persistence in emerging markets. Alti et al (2012) argue that in poor information environments (i.e. emerging markets) where there is low quality private information, investors tend to wait for subsequent confirming news to set stock prices. If that subsequent news arrives, then investors might over-estimate the precision of their private information and upwardly value the stock. In the present context, if investors believe that a company has strong operations (or believe in the volatility effect) and see a subsequent stock price gain, then they will treat it as confirmation that the stock is valuable. Over time, this effect can lead to a persistence in return trends.

Overall, we argue that the relationship between low volatility and strong operating performance might result in low volatility stocks experiencing higher stock returns. We empirically examine the hypothesis in the next section.

4. The relation between stock performance and operating performance

Bhaumik and Selarka, 2012), rather, shareholder-shareholder conflicts serve to increase the potential sources of conflict.

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This section analyzes whether strong operating performance could drive the low volatility effect. First, we discuss the methodology and sample. Next, we discuss the results.

4.1. Methodology and sample

We next analyze whether these higher stock returns also reflect superior fundamental performance. We discuss the sample and define the variables after discussing the empirical approach.

4.1.1. Models

The aim is to examine whether operating performance could explain the relation between volatility and returns, and whether 'strong operating performance' firms are more likely to be 'low volatility' firms. Our models differ from some of those used in prior studies (mainly those in Li et al., 2012). Specifically, we focus on firm-level results. The rationale is that we aim to control for firm-level factors that might otherwise drive returns. Additional advantages of this approach include: (1) Our firm-level approach is consistent with the bottom-up type of investment strategy followed by many emerging market portfolio managers, whereby they will approach factors (like size, volatility, quality etc.) in the context of other firm-level characteristics,[24] rather than by mechanically forming portfolios of high and low volatility stocks. (2) This framework also allows us to undertake robustness tests that model volatility and

[24] See for example the stated approach of Colonial First State's Emerging Market fund (Colonial First State, 2012).

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returns simultaneously, thereby addressing the possibility that volatility and returns are jointly determined.

Operating performance and volatility: Next we test whether operating performance drives volatility and vice-versa. We run several models. First, we run a Healy, Palepu and Ruback (1992) type regression of the following form:

$$\text{Operating performance}_{i,t} = \alpha + \beta I\left(\text{Volatility Quintile QM}_{i,t-1}\right) + \sum_{j=1}^{N} \theta^{j} \times \text{Controls}_{i,t-1}^{j} + \varepsilon_{i,t} \tag{1}$$

Here, the operating performance (in the reported models) is the firm's EBIT/Assets. We also report the firm's industry-adjusted EBIT/Assets, defined as the firm's EBIT/Assets less that of the firm's SIC 2-digit industry, year, and location-of-incorporation. The main volatility variable $I\left(\text{Volatility } Q\text{uintile QM}_{i,t-1}\right)$ is an indicator that equals one if the firm's volatility is in quintile QM. Quintile 1 contains the lowest volatility stocks and quintile 5 contains the highest volatility stocks. We estimate the reported models using OLS and include year dummies, stock exchange dummies, and cluster standard errors by firm. The results are also robust to using firm-level fixed effects or random effects. Table 2 Panel B contains the variable-definitions for this model.

Second, we run a logit model to predict the firm's volatility quintile as a function of its past performance (and relevant control variables). Here, the dependent variable is an indicator that equals one if the firm's volatility is in a given quintile (M) in year t.

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$$I\left(\text{Volatility Quintile QM}_{i,t}\right) = \alpha + \beta \text{Operating Performance}_{i,t-1} + \sum_{j=1}^{N} \theta^{j} \text{Controls}_{i,t-1}^{j} + \varepsilon_{i,t} \tag{2}$$

Third, we run an ordered logit model to analyze the volatility quintile in which the stock falls. Here, the dependent variable is a categorical dependent variable that comprises the five volatility quintiles.

$$\text{Volatility Quintile}_{i,t} = \alpha + \beta \text{Operating Performance}_{i,t-1} + \sum_{j=1}^{N} \theta^{j} \text{Controls}_{i,t-1}^{j} + \varepsilon_{i,t} \tag{3}$$

The models include year dummies, stock exchange dummies, and cluster standard errors by firm. Table 2 Panel B contains the variable-definitions for these models.

Operating, Volatility, and Stock Performance: We analyze the impact of volatility and operating performance on stock performance in three ways.

First, we run models to examine the determinants of monthly stock returns. These are monthly regressions that examine the firm's monthly stock return as a function of the return-spread between volatile (top volatility quintile) and stable (bottom volatility quintile) stocks, the return-spread between strong (top EBIT/Assets quintile) and weak (bottom EBIT/Assets quintile) stocks, and the SMB and HML factors for each region.[25] This induces a model of the following form:

[25] We calculate these factors for each of the four regions. The SMB factor is the equally weighted average return on the largest 20% of firms in the region that month (by market capitalization at the beginning of the month) less that of the smallest 20% of firms. The HML factor is the equally weighted average return for firms

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$$\text{Monthly Return}_{i,t} = \alpha + \beta_1(\text{stable-less-volatile}_{i,t}) + \beta_2(\text{strong-less-weak}_{i,t}) + \beta_3(\text{high-less-low}_{i,t}) + \beta_4(b\text{ig-less-small}_{i,t}) + \varepsilon_{i,t} \quad (3)$$

We also run models that test whether the relationship between (a) monthly returns, and (b) the 'stable-less-volatile' factor varies between (1) strong operating performance firms (firms with operations in the top quintile), and (2) weak operating performance firms (firms with operations in the bottom quintile).

We run the models using OLS, random effects, and fixed effects (based on firm/month panels). All models include year dummies, region dummies (for developed, emerging Asia, emerging Europe, and emerging Latin America), and cluster standard errors by firm. Table 2 Panel A contains the variable-definitions for this model.

Second, we run a yearly Fama and French (1993) type model with additional corporate control variables. Here, we also create operating performance quintiles. We create quintiles for each year and region of incorporation (developed, emerging Asia, emerging EMEA and emerging Latin America). We examine the impact of volatility quartiles and operating performance quartiles on yearly returns. We focus on yearly returns because the operating data is at a yearly frequency. We use robust regressions and quantile regressions in order to ensure that the results are robust to outliers in stock returns (following Koenker and Hallock, 2001). The models include year

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whose market capitalization/ assets is in the top 20% of the region that month less those in the bottom 20%. Similarly for the 'stable less volatile' and 'strong less weak' return-spreads.

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dummies, stock exchange dummies, and cluster standard errors by firm. Table 2 Panel B contains the variable-definitions for this model.

The goal is to analyze the extent to which the volatility effect might relate to operating performance. We do this by using Wald tests and t-tests to examine how the coefficient on the low volatility dummy changes when we control for the firm having top operating performance. This suggests the following series of models.

$$\text{Stock Return}_{i,t} = \alpha + \beta I(\text{Bottom Volatility Quintile}_{i,t-1}) + \sum_{j=1}^{N} \theta^{j} \text{Controls}_{i,t-1}^{j} + \varepsilon_{i,t} \quad (5)$$

$$\text{Stock Return}_{i,t} = \alpha + \gamma I(\text{Top Operating Quintile}_{i,t-1}) + \sum_{j=1}^{N} \theta^{j} \text{Controls}_{i,t-1}^{j} + \varepsilon_{i,t} \quad (6)$$

$$\text{Stock Return}_{i,t} = \alpha + \delta I(\text{Bottom Volatility Quintile}_{i,t-1}) + \phi I(\text{Top Operating Quintile}_{i,t-1}) + \sum_{j=1}^{N} \theta^{j} \text{Controls}_{i,t-1}^{j} + \varepsilon_{i,t} \quad (7)$$

The main point of interest is the difference between β and δ. We use Wald tests and t-tests to examine the whether the value of β equals the value of δ. A significant difference implies that some of the explanatory power associated with low volatility actually accrues to the firm having a high operating performance. We also run analogous models that examine firms with high volatility and low operating performance.

Third, we run sub-sample regressions. The sub-sample regressions examine the magnitude of the 'low volatility' dummy across sub-samples based upon operating performance. We run both

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robust regressions and quantile regressions (to address the possibility of outliers) and include year and stock-exchange dummies. Table 2 Panel B contains the variable-definitions for this model.

Fourth, we examine Chow-type tests in the context of yearly returns. We test the significance of 'low volatility' (and high volatility) across firms with strong and weak operations, and the importance of strong operations (and weak operations) across firms with high and low volatility. We do this in a robust regression framework (with year and exchange dummies, and firm clustering). An example of the models is:

$$\begin{aligned}\text{Stock Return}_{i,t} = {} & \alpha + \beta_1 I\left(\text{Top Operating Quintile}_{i,t-1}\right) + \beta_2 I\left(\text{Bottom Operating Quintile}_{i,t-1}\right) \\ & + \beta_3 I\left(\text{Bottom Volatility Quintile}_{i,t-1}\right) \\ & + \beta_4 I\left(\text{Top Operating Quintile}_{i,t-1}\right) \times I\left(\text{Bottom Volatility Quintile}_{i,t-1}\right) \\ & + \beta_5 I\left(\text{Bottom Operating Quintile}_{i,t-1}\right) \times I\left(\text{Bottom Volatility Quintile}_{i,t-1}\right) \\ & + \sum_{j=1}^{N} \theta^j \text{Controls}_{i,t-1}^{j} + \varepsilon_{i,t}\end{aligned} \quad (8)$$

We estimate similar models to examine various permutations of the volatility/operations interactions. We then use a Wald test (which collapses to a F-statistic) to examine the whether the interaction terms have the same coefficient.

Fifth, we assess the presence of the volatility effect in sub-samples of firms that do (or do not) experience operating performance improvements. We code a firm as having improved its

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operating performance if its operating performance quintile increases between year t-1 and year t. We code a firm as having a 'big' operating performance improvement if it shifts from quintile 1 or 2 to quintile 4 or 5 between year t-1 and year t. We then analyze whether the low volatility effect holds in these sub-samples. The prediction is that if operating performance gains drive the low volatility effect, then there should be no low volatility effect in the 'improving' subsample because the market will already have impounded the information associated with operating performance gains. Thus, market prices will already reflect the 'information' that is associated with the low volatility effect. Thus, low volatility should not per se increase returns in the 'improving' sub-sample.

4.1.2. Variables

This section describes the variables. The monthly models and the yearly models use different variables because they test different issues.

The monthly models focus on stock return factors. Table 2 Panel A describes their computation in detail. For each stock, we compute the monthly stock return (based upon returns data from Compustat Global). We then create several sorts based upon volatility, firm size (market capitalization), market-to-book, and operating performance. Thus, we define several return factors. Strong-less-Weak is the average return to firms with EBIT/Assets in the top quintile less that of the bottom quintile. High-less-Low is the average return for firms in the top MTB quintile less that of firms in the bottom quintile. Stable-less-Volatile is the average return to firms in the lowest volatility quintile less that for firms in the highest volatility quintile. Small-less-Big is the

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average return for firms whose market capitalization is in the bottom quintile less that of firms in the top quintile.

The yearly models aim to capture factors that influence yearly operating returns and yearly stock returns. Table 2 Panel B contains the variable definitions. The volatility measure is the firm's volatility quintile. We calculate it as follows.. For each firm we calculate the variance of the firm's daily stock return over the prior 500 days. We sort the sample based on the location of the stock exchange into the developed, emerging Asia, emerging EMEA, and emerging Latin America subsamples (as defined in Section 2). We compute the firm's rolling stock return variance over the prior 500 days. For each sub-sample and month, we classify firms into volatility quintiles. For the cross-sectional analysis, we then pick the firm's quintile classification as of the date of the firm's financial statements.

The control variables are factors that might influence operating performance and are relatively standard in the literature.[26] These include firm size, proxied by the firm's log asset; lagged operating performance; the ratio of intangibles to total assets; the ratio of debt to assets and, the firm's Tobin's Q. For the stock return models we also control for the Fama and French (1993) factors.[27] We also include country-dummies, year-dummies, and cluster standard errors by firm (consistent with Petersen, 2009). We winsorize the continuous variables at 1% to control for outliers (the results are robust to whether or not we winsorize).

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[26] See for example: Healy et al (1992), Powell and Stark (2005), Humphery-Jenner and Powell (2011)

[27] Specifically: For the SMB factor, we divide each region and year into market capitalization quintiles, and for the HML factor, we divide each region and year into Tobin's Q quintiles. We then compute the difference in yearly stock return between the top and bottom quintiles. The regions are: developed markets, emerging Asia, emerging EMEA, and emerging Latin America and are the same regions we use to compute the volatility quintiles.

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The data is from Compustat global. The total regression example comprises 128,900 observations. 38,832 of these observations are from countries that the Dow Jones classifies as 'emerging markets'. The sample spans 73 exchanges and includes companies located in 66 countries. The sample does not include the United States or Canada. The variable definitions are in Table 2 and the summary statistics are in Table 3.

[Insert Table 2 about here]

[Insert Table 3 about here]

4.2. Analysis

The results overall show that lower volatility stocks have strong operating performance, and that this holds for both emerging markets and for developed markets.

4.2.1. Does return volatility influence operating performance?

The operating performance regressions are in Table 4. The industry-adjusted operating performance results are in Table 5. The dependent variable is the one-year-ahead operating performance (in Table 4) or industry adjusted operating performance (in Table 5). The control

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variables pre-date the dependent variable.[28] The operating performance results show that the low volatility proxies are associated with higher operating performance, specifically, the indicators I(Volatility Quintile 1) and I(Volatility Quintile 2) are both positive and statistically significant. By contrast, high volatility stocks are associated with lower operating performance, with the indicators I(Volatility Quintile 4) and I(Volatility Quintile 5) being negative and statistically significant. This implies that while low volatility firms experience better operating performance, high volatility firms experience worse operating performance. Thus, while the low volatility anomaly might arise because benchmarks impose a limit on arbitrage, an additional, and complementary explanation, may be that these low volatility companies simply have stronger fundamentals.

The signs on the control variables are consistent with expectations. Large firms perform better, possibly reflecting their increased market power and stability. Firms with comparatively high market values (i.e. High Tobin's Q) perform better, likely because the high market value reflects an expectation of strong performance. Acquisitions improve performance, consistent with prior evidence that acquisitions create value for the acquirer, on average (see eg Moeller et al., 2004; Masulis et al., 2007; Humphery-Jenner and Powell, 2011). Leverage improves performance, possibly because the additional monitoring and fixed debt cash flows impose discipline upon managers to improve performance. Interestingly, intangibles reduce performance, possibly because intangibles (such as the product of on-going R&D) proxy for an on-going expense, with reduces earnings. Similarly, CAPEX reduces operating performance (likely because it is an

[28] The results are robust to being estimated in a simultaneous equation framework, where we treat the volatility variables and the operating performance variables as simultaneously determined dependent variables.

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expense that if maintained, would reduce future earnings). Lagged operating performance is positively correlated with future operating performance (as in Powell and Stark, 2005).

[Insert Table 4 about here]

[Insert Table 5. about here]

4.2.2. Does operating performance influence volatility?

The next issue is to examine whether operating performance might influence return volatility. The prediction is that strong performers tend to be larger stable companies, which will typically have lower volatility returns. We analyze operating performance as a driver of volatility by using logit and multinomial logit models.

The logit results are in Table 6. They predict the likelihood that a firm's volatility is in a given quintile as a function of prior performance and of controls. The results show that strongly performing firms are significantly more likely to have a volatility in the lowest two quintiles (i.e. Quintile 1 and Quintile 2) and are significantly less likely to have return-volatility in the top two quintiles (i.e. Quintile 4 or Quintile 5). This is consistent in both the sample of all firms and in the sample of emerging markets.

The ordered logit results are in Table 7 and support the logit results. The dependent variable is a categorical dependent variable that contains the one-year-ahead volatility quintile categories. A

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higher category indicates a higher volatility quintile.. The results show that strongly performing firms are less likely to be in a high volatility quintile.

The control variables in Table 6 and Table 7 have broadly consistent signs. Large firms are less likely to be in high volatility quintiles. Firms that have large amounts are intangibles are more likely to be in high volatility quintiles. (reflecting the fact that intangibles can be difficult for the market to value). Conversely, CAPEX-heavy firms have lower volatilities, reflecting the relation between CAPEX and fixed assets. A higher ratio of current assets to current liabilities reduces the firm's volatility (reflecting the reduced exposure to debt-based risk).

[Insert Table 6 about here]

[Insert Table 7 about here]

4.2.3. Stock returns, volatility, and operating performance:

The stock return models are in Table 8- Table 13. The models examine the impact of operating performance and volatility on stock returns. We examine monthly and yearly models. The monthly models are based on the variables in Table 2 Panel A and the yearly models are based upon the variables in Table 2 Panel B. This panel-framework contrasts with the approach of constructing volatility-based portfolios (e.g. Li et al., 2012). However, it allows us to control for firm-level characteristics that might also drive returns, and we present portfolio-like results in Section 2, where we compare the performance of portfolios of low volatility stocks and portfolios of high volatility stocks.

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Does volatility influence monthly stock returns? We first examine whether volatility influences monthly stock returns. We also examine whether this is at least in part due to operating performance factors. To do this, we examine monthly stock returns as a function of volatility, operating performance, market, size, and book-to-market factors. So, Table 8 examines the impact of operating performance and volatility on monthly stock returns. The dependent variable is the firm's monthly stock return. We report models that control for (a) the stable-less-volatile factor only, and (b) additionally control for the strong-less weak factor and the other Fama and French (1993) factors.

The main finding is that (a) the 'volatility' factor significantly influences monthly stock returns, and (b) controlling for operating performance (and the other Fama and French (1993) factors) significantly influences the relationship between the returns stable-less-volatile factor. The stable-less-volatile factor changes sign after controlling for other factors and becomes less statistically significant (being statistically insignificant in the OLS models, and significant at 5% in the fixed effects (FE) and random effects (RE) models). This (1) indicates that controlling for other corporate characteristics is important when examining the volatility/return relationship, and (2) supports the idea that operating performance might drive the relationship between volatility and returns. The difference between the figures reported in the OLS models and those in the FE/RE models is likely because the FE/RE models control for the panel structure of the data and thus account for unobserved firm-level characteristics that might make it more difficult to accurately estimate the relationship between volatility and returns.

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The other factors are also correlated with stock returns. Unsurprisingly, the coefficient on 'Region Return' is statistically significant and is close to one, suggesting both that (a) market factors drive stock returns, and (b) the average stock has a beta of one. The coefficients on the 'high-less-low' and 'small-less-big' factors are statistically significant in most models (high-less-low is insignificant in the OLS models). This result confirms the importance of size and value risk factors.

[Insert Table 8 about here]

Monthly stock return performance and the impact of volatility in operating performance quintiles: The first set of tests interact the 'volatility' factor (i.e. the spread between stable and volatile stocks) with indicators for whether the firm's operating performance is in the top or bottom quintile. The models in Table 9 aim to test how the returns/volatility relationship varies between strong operations firms and weak operations firms. The models do this by (a) interacting the stable-less-volatile factor with a top-quintile-operations indicator and a –bottom-quintile-operations indicator, and (b) testing whether the interaction terms are significantly different from one-another.

The main result is that the interactions "(Spread: Stable Less Volatile) x I(Operating Quintile 5)" and '(Spread: Stable Less Volatile) x I(Operating Quintile 1)" are significantly different from one-another (using a Wald test) in all models. The main implication is that the impact of the 'volatility' factor varies between strong-operations firms and weak-operations firms. Further, the

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negative coefficient of the term "(Spread: Stable Less Volatile) x I(Operating Quintile 1)" indicates that the positive effect of "Spread: Stable Less Volatile" on returns is not just less pronounced for firms in Operating Quintile 1, but the coefficient actually turns into negative. The coefficient on the interaction term provides further insight into the results in Table 8 (where we find that the coefficient on the "Stable-less-Volatile" factor changes in sign after controlling for other risk premiums). That is, the result sin Table 9 highlight the heterogeneous impact of volatility on stock returns and the fact that it can significantly depend on other corporate characteristics. Overall, the results imply that operating performance is an important consideration when examining the volatility effect. And, in the light of the other evidence in this paper, the results in Table 9 further support the idea that strong operations at least partially explain the volatility/returns relationship.

[Insert Table 9 about here]

Does controlling for operations weaken the volatility effect? The next set of tests examine whether the 'volatility' effect still holds after controlling for corporate operations (and vice-versa). The idea is to examine whether at least part of the 'volatility' effect is attributable to strong operating performance. We do this by examining whether the coefficients on the volatility indicators (i.e. I(Volatility Quintile 1) and I(Volatility Quintile 5)) change after controlling for operating performance.

Turning to Table 10: the models examine the impact of operating performance and volatility on stock returns. All independent variables pre-date the in dependent variable. The goal is to

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examine how the ‘low volatility’ indicator and the ‘high volatility’ indicator change after controlling for operating performance. Columns 1-3 and Columns 7-9 examine low volatility firms and Columns 4-6 and 10-12 focus on high volatility firms. The key result is that the magnitude (i.e. economic significance) of the low volatility dummy and the high volatility dummy decreases after controlling for operating performance. For example, the low-volatility dummy has a coefficient of 0.036 in Column 1, reducing to 0.027 in Column 3. Table 11 contains statistical tests to determine whether these differences are significant. The results indicate that all reductions in magnitude (in the volatility dummies) are statistically significant, implying that at least part of the low volatility effect is due to strong operating performance.

[Insert Table 10 about here]

[Insert Table 11 about here]

Does the ‘low volatility effect’ differ between strong and weak operations firms? This set of tests focuses on whether the low volatility effect (i.e. the positive relationship between I(Volatility Quintile 1) and returns) differs between subsamples of strong and weak operations firms. The idea here is that if the effect differs between strong and weak operations firms, then at least part of the volatility effect might be attributable to operating performance.

The sub-sample analysis largely confirms these results. The sub-sample regressions are in Table 12. The goal is to examine how the coefficient on the low volatility dummy changes across sub-samples of high-operations firms versus low-operations firms. The main result is that the coefficient on the ‘low volatility’ dummy is higher in the ‘low operating performance’ sub-

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sample (Columns 1 and 2) than in the ‘high-operating performance’ sub-sample (Columns 2 and 4). This implies that ‘low volatility’ has a greater impact on returns for poorly performing firms. That is, low volatility is not as impactful for high-performance firms. Table 13 presents statistical tests that indicate that the difference is statistically significant. This implies that operating performance can influence the magnitude of the low-volatility effect.

The stock returns results show that overall at least part of the low volatility effect is due to low volatility firms having higher operating performance. This comes from the fact that after controlling for operating performance there is a significant reduction in the magnitude of the low volatility effect. Similarly, the magnitude of the low volatility effect significantly varies across sub-samples based upon operating performance.

[Insert Table 12 about here]

[Insert Table 13 about here]

Table 14 contains Chow-type tests to examine the importance of volatility (across strong/weak operations firms) and of operations (across high/low volatility firms). The important variables are the interaction terms. The goal is to determine whether the interaction terms are significantly different from one-another. We find that they are statistically significantly different in all but one of the reported models. This further supports the hypothesis that operations is an important driver of the volatility/returns relationship.

[Insert Table 14 about here]

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Does the volatility effect exist for firms that experience operating performance improvements? The theory that operating performance at least partially accounts for the 'volatility effect' implies that the volatility effect should only exist for firms that do not experience an earnings improvement. That is, after controlling for the presence of an earnings surprise, there should be a weaker volatility effect because the information associated with that volatility effect is impounded into the information associated with the earnings improvement.

To address the issue of earnings surprises, we create two data-splits: (1) we split the sample by whether the firm's operating performance quintile increases between year t-1 and year t; and (2) we split the sample by whether the firm's operating performance quintile increases from 1 or 2 in year t-1 to quintile 4 or 5 in year t. We present the results in Table 15 and Table 16 below. The results show that the 'volatility effect' is either weaker or non-existent in the sample whose operating performance increases. This implies that for the sample of 'improving' firms, the volatility effect is less present. This suggests that at least part of the volatility effect is attributable to operating performance gains.

[Insert Table 15 about here]

[Insert Table 16 about here]

Overall: The results overall show that (a) firms that are in a lower volatility quintile have higher future performance, and (b) firms with high past-performance are less likely to be high volatility

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quintiles. The implication is that the stronger returns experienced by firms in lower volatility quintiles might reflect the higher operating performance that these firms experience.

4.3. Robustness tests

We ensure that the results are robust in several ways: First, the results are robust to including country-level governance and exchange-level exchange rule variables (from Cumming et al., 2011c). This should not per se be necessary because the stock exchange dummies capture unobserved country/exchange effects and most governance variables are stable (or do not change) over time. The governance variables are the ICRG composite risk index, and an equally weighted index of the ranks that the World Bank assigns to the firm's country (in the dimensions of political stability, rule of law, regulatory strength, government effectiveness, accountability, and corruption), the anti-director rights index (from Spamann, 2010), and the DLLS anti self-dealing index (from Djankov et al., 2008). The results hold when controlling for these factors. We prefer to omit governance variables from the main models because governance variables are not available for all years for all countries (and requiring exchange rules form Cumming, Johan, and Li (2011) significantly reduces the sample size) and the exchange dummies capture these factors.

Second, the results are robust to various types of clustering. Petersen (2009) and Johnson et al (2009) highlight the importance of appropriate clustering. The key results still hold whether or not the models include industry dummies, exchange dummies (as reported), year dummies (as reported), or country-of-incorporation dummies. The results hold when clustering by one or more

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of these factors (and the reported results cluster by firm, which would implicitly cluster by all factors).

Third, the results are robust to control variable definitions. They hold when replacing all book assets with market value of assets (to obtain ln(MVA), Debt/MVA, Intangibles/MVA). They also hold when replacing Tobin's Q with market to book.

Fourth, the operating performance results are robust to the definition of operating performance. Powell and Stark (2005) emphasize the importance of ensuring that results hold across different performance-specification. Our results hold when replacing EBIT with EBITDA. The results are also robust to the method of industry-adjusting. The reported models that subtract the mean operating performance for the firm's country-of-incorporation, year, and SIC 2-digit industry. However, Johnson et al (2009) highlight the importance of appropriately controlling for industry effects. Thus, we ensure that the results are robust to basing it on the location of the firm's head-quarters, and on SIC 3-digit, and 4-digit industry.

Fifth, the results are robust to the definition of an 'emerging market'; and thus, are unlikely to merely reflect sample construction issues. We focus on the broad classification in the Dow Jones. However, the results also hold when using the MSCI[29], S&P[30], or the FTSE lists.[31]

[29] These countries are Brazil, Chile, China, Colombia, Czech Republic, Egypt, Hungary, India, Indonesia, Malaysia, Mexico, Morocco, Peru, Philippines, Poland, Russia, South Africa, South Korea, Taiwan, Thailand, and Turkey.

[30] These countries are Brazil, Chile, China, Czech Republic, Egypt, Hungary, India, Indonesia, Malaysia, Mexico, Morocco, Peru, Philippines, Poland, Russia, South Africa, Taiwan, Thailand, and Turkey.

[31] FTSE has two lists of emerging markets. The 'advanced' emerging markets are Brazil, China, Hungary, Mexico, Turkey, Poland, South Africa, Taiwan, and Malaysia. The secondary emerging markets are Chile, Colombia, Czech Republic, Philippines, Egypt, Indonesia, Morocco, Peru, Russia, Thailand, Turkey, and UAE.

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Sixth, the results are robust to the method of computing the volatility quintiles. One concern is that different stock exchanges have different market microstructures, trading rules, and have different levels of direct market access/ high frequency trading (HFT). This is an issue because HFT, for example, actively takes advantage of volatility movements (see Bialkowski et al., 2008; Brownlees et al., 2011; Florackis et al., 2011; Humphery-Jenner, 2011b). The results are economically similar whether we compute the volatility quintiles for each exchange, geographic region, or by simple emerging/developed distinction.

Seventh, the results are robust to controlling for proxies for trading costs. Li et al (2012) suggest that the low volatility effect is attributable to trading cost concerns. We address this (in unreported robustness tests) by also controlling for the a proxy for trading costs: the proportion of days on which there is zero return (following Lesmond et al., 1999). Our results are qualitatively robust to controlling for the trading cost proxy.

5. Conclusion

This paper provides international evidence that low volatility stocks have higher stock returns, and shows that this may reflect the fact that low volatility firms have higher operating performance. Prior studies show that low volatility stocks in the US have higher stock returns. One explanation is that the low volatility effect arises because benchmarking of institutional money management mandates creates limits to arbitrage. This explanation would be valid to varying degrees in different geographies, and particularly so in emerging markets, where there is

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both a less institutionalized fund management industry but where low volatility stocks are more likely to feature in any index benchmark.

We propose that operating performance can be an additional explanation for the low volatility effect. Low volatility firms tend to have strong operating returns. Strong operating returns would increase expected stock returns. If the strong operating performance is unexpected, then it would drive investors to bid up the stock price. Otherwise, the operating performance would yield higher cash flows, which the firm could use to aggressively pursue expansion opportunities. This would especially hold in emerging markets, where there are fewer constraints on managerial activities. These investments would increase corporate risk and drive up expected returns.

We find evidence for our hypothesis in an international sample. We expand upon the findings in Baker, Bradley, and Wurgler (2011) by examining international stock returns and by providing an additional explanation for the low volatility effect. We show that the low volatility effect exists across most markets outside the US, including in emerging markets. We also show that (a) part of the stable-less-volatility stock return spread is attributable to operating performance, (b) low-volatility stocks have stronger future operating performance, and (c) strong past operating performance can help predict whether a firm will be a low volatility stock in the future, an (d) that controlling for operating performance significantly influences the relationship between stock returns and volatility. This implies that higher operating performance is an additional possible explanation for the low volatility effect. This can operate along-side the benchmarking explanation proposed in Baker, Bradley, and Wurgler (2011).

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6. Figures and tables

Figure 1: Value of $1 Invested in 1995 – Value Weighted Portfolios

This figure contains the value of $1 invested in 1995. We sort the sample into volatility quintile portfolios based upon the stock's volatility over the prior twelve months. We rebalance the portfolios ever month. The returns are value-weighted with the value-weighting being the stocks relative contribution to the overall USD market capitalization of its quintile-portfolio.

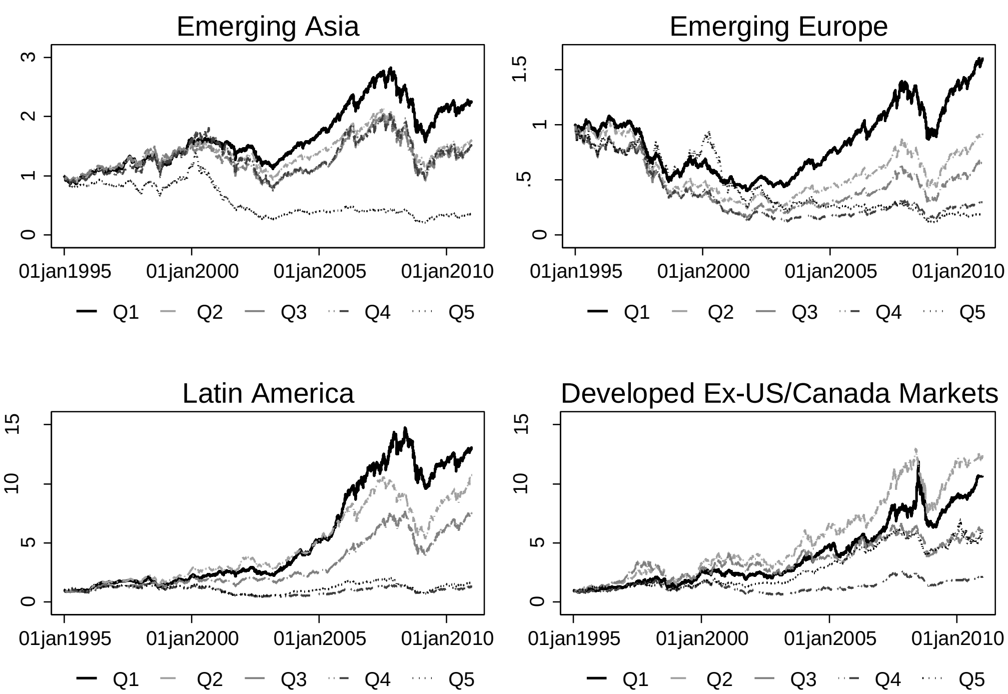

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Figure 2: Value of $1 Invested in 1995 – Equally Weighted Portfolios

This figure contains the value of $1 invested in 1995. We sort the sample into volatility quintile portfolios based upon the stock's volatility over the prior twelve months. We rebalance the portfolios ever month.

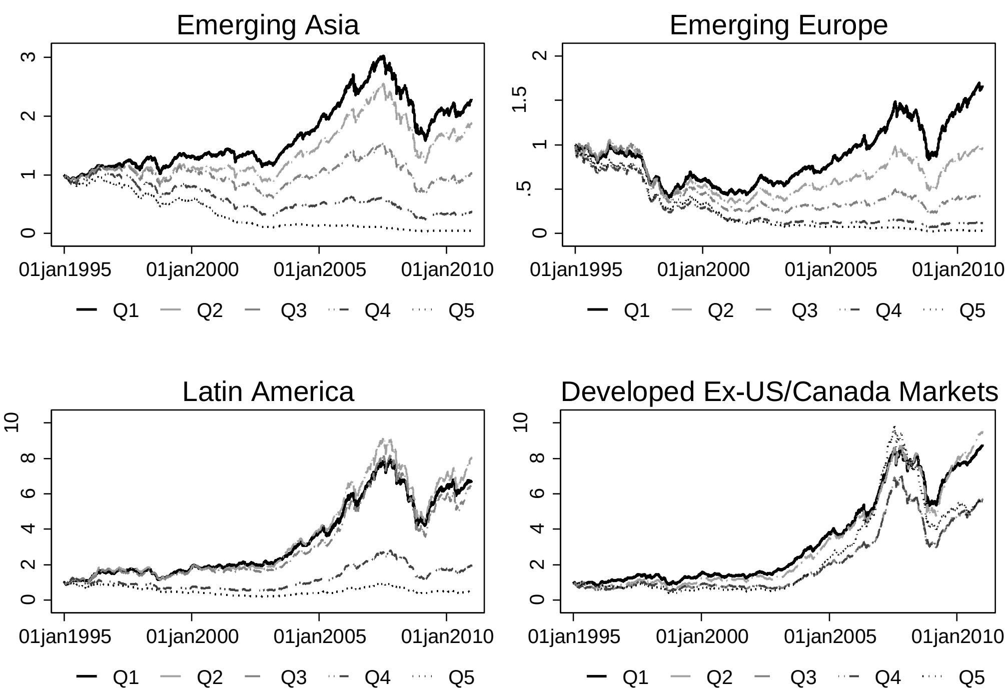

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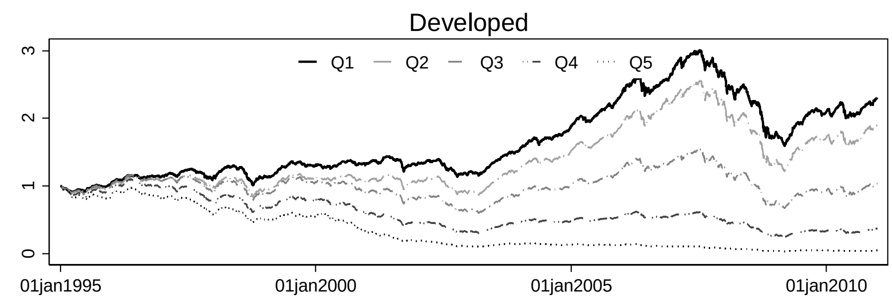
Figure 3: Equally weighted portfolios by emerging and developed markets

This figure contains the value of $1 invested in 1995 split by whether the stock is in a developed market or an emerging market. We sort the sample into volatility quintile portfolios based upon the stock's volatility over the prior twelve months. We rebalance the portfolios ever month.



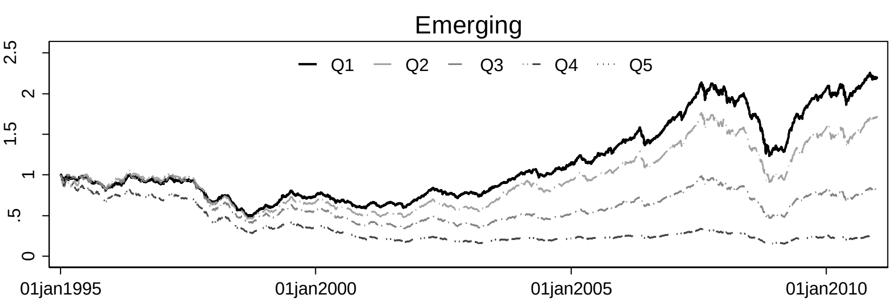


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Figure 4: Average Yearly Returns

This figure reports the average yearly return earned in each value-weighted quintile-portfolio in each region.

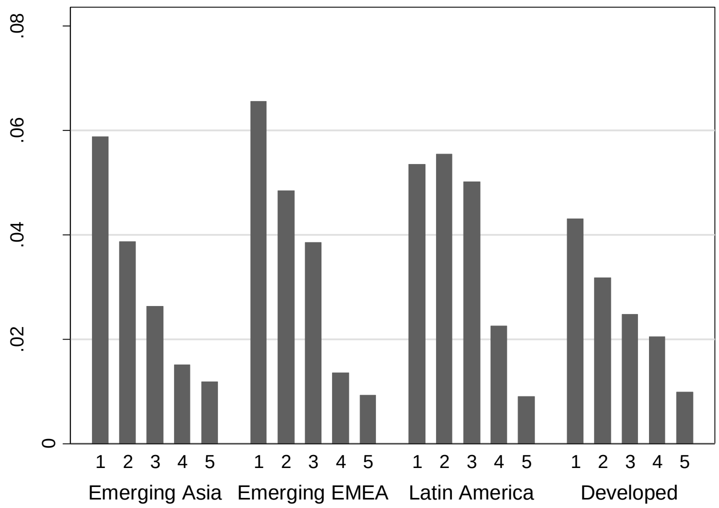

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Table 1: Average Yearly Returns

This Exhibit contains the average yearly value-weighted returns. We construct portfolios for each sample based on the firm's 500 day stock return variance. We drop firms whose USD market capitalization is in the bottom 10% of the firm's stock-exchange-country, or whose turnover is in the bottom 10% of the region. We compute value-weighted returns based on the contribution of the firm's USD market capitalization to the overall USD market capitalization of the region.

Quintile	All	Emerging Asia	Emerging EMEA	Latin America	Developed
1 (Lowest Volatility)	0.055	0.059	0.066	0.053	0.043
2	0.044	0.039	0.048	0.055	0.032
3	0.035	0.026	0.039	0.050	0.025
4	0.018	0.015	0.014	0.023	0.021
5 (Highest Volatility)	0.010	0.012	0.009	0.009	0.010
Overall	0.032	0.030	0.035	0.038	0.026

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Table 2: Variable Definitions

Variable	Definition
Panel A: Monthly return regressions	
Stable-less-volatile	The monthly stock return spread between stocks in the lowest stock variance quintile and stocks in the highest stock variance quintile. We compute it as follows. First, divide the sample into regions (emerging Asia, emerging, Europe, emerging Latin America, and developed) and months. Second, for each stock, compute the stock return variance over the prior 500 days. Third, for each region/month sort, generate quintiles based upon the stock return variance over the prior 500 days. Fourth, over the next month, compute the equally weighted average of the returns for firms in each quintile. Fifth, compute the difference between the lowest volatility quintile and the highest volatility quintile.
Strong-less-weak	The monthly stock return spread between stocks in highest operating performance quintile and stocks in the lowest operating performance quintile. We compute it as follows. First, divide the sample into regions (emerging Asia, emerging, Europe, emerging Latin America, and developed) and months. Second, for each stock compute the firm's EBIT/Assets from the latest annual report (as indicated in Compustat global). Third, for each region/month sort, generate quintiles based on EBIT/Assets. Fourth, over the next month, compute the equally weighted average of the returns for firms in each quintile. Fifth, compute the difference between the highest EBIT/Assets quintile and the lowest EBIT/Assets quintile.
High-less-low	The monthly stock return spread between stocks in highest market-to-book quintile and stocks in the lowest market-to-book quintile. We compute it as follows. First, divide the sample into regions (emerging Asia, emerging, Europe, emerging Latin America, and developed) and months. Second, for each stock compute the firm's market capitalization/Assets based upon the market capitalization at the beginning of the month and the assets from the latest annual report (as indicated in Compustat global). Third, for each region/month sort, generate quintiles based on market-to-book. Fourth, over the next month, compute the equally weighted average of the returns for firms in each quintile. Fifth, compute the difference between the highest quintile and the lowest quintile.
Small-less-big	The monthly stock return spread between stocks in highest market capitalization quintile and stocks in the lowest market capitalization quintile. We compute it as follows. First, divide the sample into regions (emerging Asia, emerging, Europe, emerging Latin America, and developed) and months. Second, for each stock compute the firm's market capitalization based upon the market capitalization at the beginning of the month. Third, for each region/month sort, generate quintiles based on market capitalization. Fourth, over the next month, compute the equally weighted average of the returns for firms in each quintile. Fifth, compute the difference smallest market cap quintile and the largest market cap quintile
Region return	The equally weighted average stock return of all firms in the company's region and month.
Panel B: Yearly regressions	
I(Volatility Quintile M)	An indicator that equals one if the firm is in volatility quintile M for the year. Quintile 1 contains the lowest volatility stocks and quintile 5 contains the highest volatility stocks. We calculate it as follows: For each stock we calculate the variance of the daily stock returns over the past 500 days. For each exchange, we sort the variances into quintiles. We then assign an indicator

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	variable that equals one if the firm's volatility is in the M during the prior year.
ln(Assets)	The natural log of the firm's book assets (Compustat code: at)
EBIT/Assets	The firm's EBIT divided by its book assets (Compustat codes: ebit/at)
Ind Adj EBIT/Assets	The firm's EBIT/Assets less that of the firm's SIC 2-digit industry, year, and location-of-incorporation.
Tobin's Q	The firm's market value of assets divided by its book assets. The market value of assets is the share price multiplied by the shares outstanding (Compustat code: cshoi) plus the book assets (Compustat code: at) less the book equity (Compustat code: ceq). The share price is the price reported by Compustat global on the month and year of the firm's financial statements.
Current Assets/ Current Liabilities	The firm's current assets (Compustat code: act) divided by its current liabilities (Compustat code: lct)
I(Acquisition)	An indicator that equals one if Compustat indicates that the firm made a takeover of some type in the year.
Debt/Assets	The firm's long term debt scaled by its book assets (Compustat codes: dltt/at)
Intangibles/Assets	The firm's intangible assets scaled by its book assets (Compustat codes: intan/at). Following Masulis, Wang and Xie (2009) we treat a missing intangibles number as zero.
CAPEX/Sales	The firm's capital expenditure scaled by its sales (Compustat codes: capx/sales)

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Table 3: Summary Statistics

This Table contains summary statistics for the models. Table 2 contains the variable definitions.

Variable	Mean	Median	Min	Max	Std Dev
Panel A: Monthly Regressions					
Monthly Stock Return	0.031	-0.001	-0.767	3.405	0.322
Stable-less-Volatile	0.011	0.008	-1.206	1.437	0.117
Strong-less-Weak	0.030	0.024	-0.278	1.289	0.075
High-less-Low	-0.067	-0.034	-2.113	0.283	0.182
Small-less-Big	0.077	0.047	-0.283	4.172	0.111
Monthly Stock Return	0.031	-0.001	-0.767	3.405	0.322
Panel B: Yearly Regressions					
ln(Assets)	7.838	7.725	1.213	15.581	3.265
EBIT/Assets	0.032	0.050	-0.811	0.317	0.149
Tobin's Q	2.326	1.135	0.423	66.393	7.011
Current Assets/ Current Liabilities	2.280	1.478	0.233	21.260	2.883
I(Acquisition)	0.168	0.000	0.000	1.000	0.374
Debt/Assets	0.118	0.073	0.000	0.597	0.134
Intangibles/Assets	0.071	0.009	0.000	0.686	0.138
CAPEX/Sales	0.138	0.035	0.000	4.151	0.481

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Table 4: Regressions examining the drivers of operating performance

This Table contains the operating performance regressions. The dependent variable is the firm's operating performance in year *t*. All independent variables are lags. The models are OLS models and include year dummies, stock-exchange dummies, and cluster standard errors by firm. Columns 1-5 examine the whole sample. Columns 6 – 10 examine a sub-sample of firms that trade on exchanges in emerging markets, as classified by Dow Jones. Table 2 (Panel B) contains the variable definitions. Brackets contain p-values. Superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Sample	Full Sample					Dow Jones Emerging Markets				
Dependant Variable	EBIT/Assets x 100									
Model	OLS, Year Dummies, Exchange Dummies, Firm clustering									
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
I(Volatility Quintile 1)	1.031***					1.250***				
	[0.000]					[0.000]				
I(Volatility Quintile 2)		0.511***					0.282***			
		[0.000]					[0.000]			
I(Volatility Quintile 3)			0.148***					-0.146		
			[0.006]					[0.115]		
I(Volatility Quintile 4)				-0.389***					-0.603***	
				[0.000]					[0.000]	
I(Volatility Quintile 5)					-1.478***					-1.067***
					[0.000]					[0.000]
ln(Assets)	0.291***	0.305***	0.316***	0.311***	0.255***	0.167***	0.210***	0.215***	0.207***	0.167***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
EBIT/Assets	68.518***	68.705***	68.786***	68.780***	68.071***	64.925***	65.578***	65.643***	65.477***	65.097***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Tobin's Q	0.016***	0.017***	0.017***	0.017***	0.017***	0.012***	0.013***	0.013***	0.013***	0.012***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.003]	[0.001]	[0.001]	[0.001]	[0.002]
Current Assets/ Current Liabilties	-0.335***	-0.336***	-0.335***	-0.336***	-0.327***	0.001	0.007	0.008	0.006	0.005
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.957]	[0.793]	[0.776]	[0.830]	[0.836]
I(Makes an Acquisition)	0.190**	0.196**	0.207**	0.205**	0.164*	0.103	0.132	0.136	0.126	0.117
	[0.040]	[0.035]	[0.026]	[0.028]	[0.076]	[0.456]	[0.342]	[0.326]	[0.363]	[0.399]
Debt/Assets	0.670***	0.755***	0.717***	0.729***	0.778***	-0.635*	-0.788**	-0.818**	-0.765**	-0.640*
	[0.006]	[0.002]	[0.003]	[0.003]	[0.001]	[0.076]	[0.028]	[0.022]	[0.033]	[0.073]
Intangibles/Assets	-2.996***	-3.070***	-3.093***	-3.084***	-2.921***	-0.697	-0.77	-0.795	-0.733	-0.741
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.306]	[0.259]	[0.245]	[0.283]	[0.279]
CAPEX/Sales	-1.192***	-1.201***	-1.208***	-1.213***	-1.135***	-0.876***	-0.879***	-0.875***	-0.876***	-0.886***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Constant	-1.053	-1.157	-1.185	-1.009	-0.266	0.336	0.287	0.351	0.507	0.748
	[1.000]	[.]	[.]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
Observations	128,900	128,900	128,900	128,900	128,900	38,832	38,832	38,832	38,832	38,832
R-squared	54.20%	54.20%	54.10%	54.20%	54.30%	44.80%	44.60%	44.60%	44.60%	44.70%

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Table 5: Regressions examining the drivers of industry adjusted operating performance

This Table contains the operating performance regressions that 'industry adjust' the firm's operating performance. The dependent variable is the firm's industry adjusted operating performance in year *t*. All independent variables are lags. The models are OLS models and include year dummies, stock-exchange dummies, and cluster standard errors by firm. Columns 1-5 examine the whole sample. Columns 6 – 10 examine a sub-sample of firms that trade on exchanges in emerging markets, as classified by Dow Jones. Table 2 (Panel B) contains the variable definitions. Brackets contain p-values. Superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Sample	Full Sample					Dow Jones Emerging Markets				
Dependant Variable	Ind Adj EBIT/Assets x 100									
Model	OLS, Year Dummies, Exchange Dummies, Firm clustering									
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
I(Volatility Quintile 1)	0.680***					1.000***				
	[0.000]					[0.000]				
I(Volatility Quintile 2)		0.364***					0.249***			
		[0.000]					[0.001]			
I(Volatility Quintile 3)			0.138***					-0.156*		
			[0.006]					[0.061]		
I(Volatility Quintile 4)				-0.305***					-0.434***	
				[0.000]					[0.000]	
I(Volatility Quintile 5)					-0.995***					-0.901***
					[0.000]					[0.000]
ln(Assets)	0.208***	0.218***	0.226***	0.222***	0.181***	0.109***	0.146***	0.150***	0.144***	0.108***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Ind Adj EBIT/Assets	66.485***	66.566***	66.605***	66.609***	66.230***	61.960***	62.433***	62.491***	62.380***	62.054***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Tobin's Q	0.015***	0.015***	0.015***	0.015***	0.015***	0.007**	0.008**	0.008**	0.008**	0.007**
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.030]	[0.010]	[0.011]	[0.011]	[0.023]
Current Assets/ Current Liabilities	-0.233***	-0.234***	-0.234***	-0.235***	-0.227***	0.009	0.014	0.015	0.014	0.013
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.698]	[0.555]	[0.541]	[0.578]	[0.600]
I(Makes an Acquisition)	0.063	0.068	0.076	0.074	0.043	0.033	0.057	0.061	0.054	0.044
	[0.460]	[0.430]	[0.377]	[0.387]	[0.614]	[0.792]	[0.649]	[0.628]	[0.668]	[0.727]
Debt/Assets	-0.17	-0.114	-0.14	-0.132	-0.095	-0.940***	-1.073***	-1.101***	-1.060***	-0.939***
	[0.445]	[0.611]	[0.529]	[0.555]	[0.669]	[0.002]	[0.001]	[0.000]	[0.001]	[0.002]
Intangibles/Assets	-2.145***	-2.198***	-2.216***	-2.209***	-2.081***	-0.967	-1.023*	-1.044*	-1.001*	-1.000*
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.111]	[0.092]	[0.086]	[0.099]	[0.100]
CAPEX/Sales	-0.469***	-0.478***	-0.484***	-0.488***	-0.423***	-0.598***	-0.602***	-0.599***	-0.599***	-0.606***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Constant	-1.515	-1.59	-1.616	-1.475	-0.974	-1.436	-1.461	-1.398	-1.298	-1.084
	[.]	[0.999]	[.]	[1.000]	[.]	[1.000]	[1.000]	[1.000]	[1.000]	[1.000]
Observations	128,900	128,900	128,900	128,900	128,900	38,832	38,832	38,832	38,832	38,832
R-squared	45.70%	45.70%	45.70%	45.70%	45.80%	37.30%	37.10%	37.10%	37.20%	37.20%

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Table 6: Logit Models predicting volatility quintiles

This Table contains logit models that predict the firm's one-year ahead volatility quintile. The models are logits, include year dummies, exchange dummies, and cluster standard errors by firm. Columns 1-5 examine the sample of all firms. Columns 6-10 examine a sub-sample of firms that trade on exchanges in emerging markets (as classified by Dow Jones). Table 2 (Panel B) contains the variable definitions. Brackets contain p-values. Superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Sample			All Markets					Emerging Markets		
Dependent Variable	I(Q1)	I(Q2)	I(Q3)	I(Q4)	I(Q5)	I(Q1)	I(Q2)	I(Q3)	I(Q4)	I(Q5)
Model				Logit, Year Dummies, Exchange Dummies, Firm clustering						
Column	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
ln(Assets)	0.185***	0.134***	0.048***	-0.100***	-0.428***	0.293***	0.089***	0.025**	-0.082***	-0.392***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.030]	[0.000]	[0.000]
EBIT/Assets	4.848***	2.288***	1.047***	-0.208***	-2.931***	6.092***	2.492***	0.464***	-1.215***	-4.191***
	[0.000]	[0.000]	[0.000]	[0.004]	[0.000]	[0.000]	[0.000]	[0.003]	[0.000]	[0.000]
Tobin's Q	-0.001	-0.001	-0.001	0	-0.011***	0.011***	0.001	0	0	-0.010***
	[0.638]	[0.644]	[0.390]	[0.912]	[0.000]	[0.001]	[0.656]	[0.770]	[0.947]	[0.000]
Current Assets/ Current Liabilities	-0.006	0.003	-0.014***	-0.009**	0.028***	0.035***	0.021***	-0.01	-0.035***	-0.039***
	[0.381]	[0.505]	[0.000]	[0.027]	[0.000]	[0.000]	[0.003]	[0.217]	[0.001]	[0.001]
I(Makes an Acquisition)	0.101***	0.159***	0.033	0.017	-0.171***	0.132**	0.214***	-0.012	-0.065	-0.292***
	[0.002]	[0.000]	[0.188]	[0.523]	[0.000]	[0.014]	[0.000]	[0.806]	[0.223]	[0.000]
Debt/Assets	0.217*	-0.551***	-0.228***	0.411***	0.831***	-1.241***	-0.666***	0.061	0.619***	1.591***
	[0.073]	[0.000]	[0.002]	[0.000]	[0.000]	[0.000]	[0.000]	[0.617]	[0.000]	[0.000]
Intangibles/Assets	-0.697***	-0.231***	0.122	0.296***	1.049***	-0.53	-0.606***	0.272	0.578***	0.393
	[0.000]	[0.006]	[0.147]	[0.001]	[0.000]	[0.142]	[0.006]	[0.223]	[0.009]	[0.161]
CAPEX/Sales	-0.213***	-0.170***	-0.046*	-0.050**	0.273***	-0.007	0.092*	0.009	0.018	-0.074
	[0.000]	[0.000]	[0.067]	[0.035]	[0.000]	[0.932]	[0.086]	[0.861]	[0.752]	[0.289]
Constant	-7.727***	-6.435***	-5.320***	-4.488***	-2.761***	-8.625***	-5.664***	-4.948***	-3.985***	-1.031
	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.210]
Observations	148,722	148,763	148,829	148,820	148,420	45,625	45,625	45,646	45,639	45,402
Pseudo R-squared	17.00%	7.00%	5.00%	6.00%	25.00%	17.00%	6.00%	5.00%	6.00%	16.00%

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Table 7: Ordered logit models examining volatility quintiles

This Table contains ordered logit models that predict the firm's volatility quintile. The dependent variable is a categorical dependent variable that contains the firm's volatility quintile. There are five categories. The models include year dummies, exchange dummies, and cluster standard errors by firm. Column 1 examines all firms. Column 2 contains firms that trade on exchanges in emerging markets. Table 2 (Panel B) contains the variable definitions. Brackets contain p-values. Superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Sample	All	Emerging Markets
Dependent Variable	Volatility Quintile	
Model	Ordered Logit, Year Dummies, Exchange Dummies, Firm Clustering	
Column	[1]	[2]
ln(Assets)	-0.264***	-0.296***
	[0.000]	[0.000]
EBIT/Assets	-4.380***	-6.053***
	[0.000]	[0.000]
Tobin's Q	-0.002	-0.007***
	[0.178]	[0.000]
Current Assets/ Current Liabilities	0.013***	-0.045***
	[0.001]	[0.000]
I(Makes an Acquisition)	-0.165***	-0.199***
	[0.000]	[0.000]
Debt/Assets	0.369***	1.358***
	[0.000]	[0.000]
Intangibles/Assets	0.844***	0.631***
	[0.000]	[0.008]
CAPEX/Sales	0.293***	-0.063
	[0.000]	[0.238]
Constant/ Cut 1	-4.984***	-5.192***
	[0.000]	[0.000]
Constant/ Cut 2	-3.590***	-3.906***
	[0.000]	[0.000]
Constant/ Cut 3	-2.432***	-2.826***
	[0.000]	[0.000]
Constant/ Cut 4	-1.015*	-1.491**
	[0.072]	[0.012]
Observations	129,232	38,957
Pseudo R-squared	12.00%	9.00%

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Table 8: Regressions examining determinants of monthly stock returns

This Table contains the results of monthly stock return regressions. The models focus on the monthly stock return. The key variables of interest are the stable-less-volatile variable and the strong-less-weak variable. The column title states the modeling technique, where OLS means ordinarily least squares, RE means random effects, and FE means fixed effects, where the panels are stock/month panels. Table 2 (Panel A) contains the variable definitions. Brackets contain p-values and superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Modeling Technique	OLS	OLS	RE	RE	FE	FE
Column	[1]	[2]	[3]	[4]	[5]	[6]
Dependent Variable			Stock Return			
Spread: Stable-less-Volatile	-0.528***	0.011	-0.550***	0.025**	-0.543***	0.023**
	[0.000]	[0.374]	[0.000]	[0.022]	[0.000]	[0.034]
Spread: Strong-less-Weak		-0.030***		-0.033***		-0.031***
		[0.010]		[0.002]		[0.004]
Region Return		1.012***		1.014***		1.014***
		[0.000]		[0.000]		[0.000]
Spread: High-less-Low		0.007		0.024***		0.021***
		[0.303]		[0.000]		[0.000]
Spread: Small-less-Big		-0.027**		-0.037***		-0.036***
		[0.017]		[0.000]		[0.000]
Constant	-0.020***	-0.014***	-0.002	-0.023***	0.042***	-0.010***
	[0.000]	[0.001]	[0.425]	[0.000]	[0.000]	[0.000]
Observations	1,706,333	1,706,333	1,706,333	1,706,333	1,706,333	1,706,333
R-squared	2.20%	5.00%	2.20%	5.20%		
R-Squared (overall)			2.10%	4.90%	2.20%	4.90%
R-Squared (within)			2.17%	5.17%	2.17%	5.17%
R-Squared (between)			1.72%	3.63%	2.16%	4.26%

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Table 9: Monthly returns and the interaction of return-volatility and operating performance

This Table contains models that examine how the relationship between returns and the 'Stable-less-Volatile' spread varies between high operations (strong) firms and low operations (weak) firms. The column title states the model (OLS, random effects, or fixed effects, based on firm/month panels). All models include year dummies and region dummies and cluster standard errors by firm. Brackets contain p-values and superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Model	OLS	RE	FE
Dependent Variable		Monthly Return	
Column	[1]	[2]	[3]
I(Operating Quintile 1)	-0.010***	-0.013***	-0.015***
	[0.000]	[0.000]	[0.000]
I(Operating Quintile 5)	0.008***	0.013***	0.014***
	[0.000]	[0.000]	[0.000]
Spread: Stable Less Volatile	0.062***	0.085***	0.089***
	[0.000]	[0.000]	[0.000]
(Spread: Stable Less Volatile) x I(Operating Quintile 5)	0.000	0.001	0.002
	[0.989]	[0.965]	[0.901]
(Spread: Stable Less Volatile) x I(Operating Quintile 1)	-0.251***	-0.304***	-0.315***
	[0.000]	[0.000]	[0.000]
Spread: Strong Less Weak	-0.031***	-0.032***	-0.034***
	[0.007]	[0.003]	[0.002]
Region Return	1.012***	1.015***	1.014***
	[0.000]	[0.000]	[0.000]
Spread: High Less Low	0.007	0.023***	0.026***
	[0.259]	[0.000]	[0.000]
Spread: Small Less Big	-0.026**	-0.037***	-0.039***
	[0.021]	[0.000]	[0.000]
Constant	-0.013***	-0.010***	-0.021***
	[0.002]	[0.000]	[0.000]
Observations	1,706,333	1,706,333	1,706,333
R-squared	5.05%		
R-Squared Overall		5.02%	4.99%
R-Squared Within		5.30%	5.30%
R-Squared Between		4.03%	3.60%
Wald Tests			
Test Statistic	84.40***	292.01***	313.19***
	[0.000]	[0.000]	[0.000]

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Table 10: Regressions examining the determinants of yearly stock returns

This table contains models that examine the impact of volatility and operating performance on stock returns. The models in Columns 1-6 are quantile regressions (based upon a 50% quantile of returns; that is, they examine the factors that influence the changes in the median). The models in Columns 7-12 are robust regressions. The models also include year dummies and stock exchange dummies. Brackets contain p-values and superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Dependent Variable	Yearly Stock Return											
	Quantile Regression						Robust Regression					
Column	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
I(Volatility Quintile 1)	0.036***		0.027***				0.047***		0.039***			
	[0.000]		[0.000]				[0.000]		[0.000]			
I(Operating Quintile 5)		0.083***	0.081***					0.097***	0.094***			
		[0.000]	[0.000]					[0.000]	[0.000]			
I(Volatility Quintile 5)				-0.054***		-0.028***				-0.091***		-0.062***
				[0.000]		[0.000]				[0.000]		[0.000]
I(Operating Quintile 1)					-0.137***	-0.132***					-0.165***	-0.155***
					[0.000]	[0.000]					[0.000]	[0.000]
SMB	-0.027***	-0.027***	-0.028***	-0.023***	-0.018**	-0.018**	0.002	0	0	0.001	0	-0.001
	[0.001]	[0.000]	[0.000]	[0.003]	[0.013]	[0.010]	[0.825]	[0.961]	[0.948]	[0.939]	[0.963]	[0.900]
HML	-0.011	-0.011	-0.012	-0.007	-0.006	-0.007	0.068***	0.070***	0.070***	0.068***	0.073***	0.072***
	[0.340]	[0.306]	[0.284]	[0.522]	[0.571]	[0.522]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Market Return	0.760***	0.764***	0.761***	0.764***	0.757***	0.759***	0.714***	0.713***	0.711***	0.708***	0.705***	0.702***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ln(Assets)	0.012***	0.013***	0.012***	0.011***	0.008***	0.006***	0.016***	0.017***	0.016***	0.013***	0.010***	0.008***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Tobin's Q	-0.005***	-0.006***	-0.006***	-0.005***	-0.005***	-0.005***	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Current Assets/ Current Liabilities	-0.003***	-0.004***	-0.004***	-0.003***	-0.002***	-0.002***	-0.002***	-0.003***	-0.003***	-0.002***	-0.001	-0.001
	[0.000]	[0.000]	[0.000]	[0.000]	[0.006]	[0.006]	[0.000]	[0.000]	[0.000]	[0.002]	[0.149]	[0.365]
I(Makes an Acquisition)	0.008*	0.009**	0.008*	0.008*	0.003	0.003	0.020***	0.021***	0.020***	0.019***	0.013***	0.012***
	[0.085]	[0.042]	[0.085]	[0.081]	[0.497]	[0.443]	[0.000]	[0.000]	[0.000]	[0.000]	[0.002]	[0.006]
Debt/Assets	-0.036***	-0.004	-0.004	-0.027**	-0.026**	-0.024**	-0.054***	-0.016	-0.019*	-0.045***	-0.040***	-0.037***
	[0.004]	[0.746]	[0.728]	[0.024]	[0.027]	[0.028]	[0.000]	[0.166]	[0.096]	[0.000]	[0.000]	[0.001]
Intangibles/Assets	-0.160***	-0.167***	-0.161***	-0.166***	-0.146***	-0.145***	-0.170***	-0.167***	-0.163***	-0.161***	-0.149***	-0.141***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
CAPEX/Sales	-0.005	0.002	0.004	-0.003	0.012***	0.014***	-0.023***	-0.016***	-0.015***	-0.018***	-0.004	-0.001
	[0.211]	[0.647]	[0.255]	[0.315]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.196]	[0.785]
Constant	-1.447***	-1.207***	-1.230***	-0.976***	-0.442*	-1.157***	-0.96	-0.886	-0.919	0.11	-0.889	0.129
	[0.000]	[0.000]	[0.000]	[0.000]	[0.093]	[0.000]	[1.000]	[0.999]	[0.999]	[1.000]	[1.000]	[1.000]
Observations	134,950	134,950	134,950	134,950	134,950	134,950	134,949	134,950	134,950	134,950	134,949	134,950
Pseudo R-Squared	7.09%	7.22%	7.24%	7.11%	7.41%	7.42%	14.60%	15.00%	15.00%	14.90%	15.80%	15.90%

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Table 11: Test Statistics for the models in Table 10

This Table contains test statistics based upon the models in Table 10. Brackets contain p-values. The Table tests hypotheses about the coefficients on the regressions. Superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Null Hypothesis	t-tests Test Statistic	Wald Tests Test Statistic
H0: Column 1 I(Volatility Quintile 1) = Column 3 I(Volatility Quintile 1) = 0.027	2.07***	4.08**
	[0.000]	[0.044]
H0: Column 4 I(Volatility Quintile 5) = Column 6 I(Volatility Quintile 5) = -0.028	-6.42***	43.36***
	[0.000]	[0.000]
H0: Column 7 I(Volatility Quintile 1) = Column 9 I(Volatility Quintile 1) = 0.039	2.05***	4.75**
	[0.000]	[0.029]
H0: Column 10 I(Volatility Quintile 5) = Column 12 I(Volatility Quintile 5) = -0.062	-7.53***	55.48***
	[0.000]	[0.000]

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Table 12: Sub-sample stock return regressions

This Table contains the results of regressions that analyze sub-samples based upon operating performance. Columns 1 and 3 examine firms whose operating performance is in the lowest two quintiles. Columns 2 and 4 examine firms whose operating performance is in the top two quintiles. Columns 1 and 2 use quantile regressions and Columns 3 and 4 use robust regressions. Table 2 contains the variable definitions Brackets contain p-values. Superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Operating Performance Quintiles	Q1 and Q2	Q4 and Q5	Q1 and Q2	Q4 and Q5
Model	Quantile Regression		Robust Regression	
Column	[1]	[2]	[3]	[4]
I(Volatility Quintile 1)	0.042***	0.011**	0.045***	0.023***
	[0.000]	[0.049]	[0.000]	[0.000]
SMB	-0.008	-0.011	-0.002	0.011
	[0.485]	[0.349]	[0.851]	[0.339]
HML	-0.003	0.030*	0.059***	0.080***
	[0.868]	[0.077]	[0.001]	[0.000]
Market Return	0.865***	0.696***	0.715***	0.701***
	[0.000]	[0.000]	[0.000]	[0.000]
ln(Assets)	0.015***	0.000	0.023***	0.001
	[0.000]	[0.880]	[0.000]	[0.602]
Tobin's Q	-0.004***	-0.006***	-0.004***	-0.008***
	[0.000]	[0.000]	[0.000]	[0.000]
Current Assets/ Current Liabilities	-0.001	-0.007***	0.002**	-0.008***
	[0.408]	[0.000]	[0.028]	[0.000]
I(Makes an Acquisition)	-0.001	0.005	0.009	0.01
	[0.934]	[0.404]	[0.223]	[0.101]
Debt/Assets	-0.053***	0.03	-0.081***	0.021
	[0.003]	[0.123]	[0.000]	[0.261]
Intangibles/Assets	-0.214***	-0.085***	-0.194***	-0.104***
	[0.000]	[0.000]	[0.000]	[0.000]
CAPEX/Sales	0.012***	-0.049***	-0.001	-0.050***
	[0.001]	[0.002]	[0.848]	[0.001]
Constant	-0.861***	1.887***	-0.25	-0.067
	[0.000]	[0.000]	[1.000]	[1.000]
Observations	52,750	54,968	52,748	54,968
Pseudo R-Squared	7.00%	6.92%	14.50%	14.70%

Table 13: Hypothesis tests for Table 12

This Table tests hypotheses about the coefficients in Table 12. Brackets contain p-values and superscript *** denotes significance at 1%.

Null Hypothesis	t-tests Test Statistic	Wald Tests Test Statistic
H0: Column 1 I(Volatility Quintile 1) = Column 2 I(Volatility Quintile 1) = 0.011	3.92***	15.08***
	[0.000]	[0.000]
H0: Column 3 I(Volatility Quintile 5) = Column 4 I(Volatility Quintile 5) = 0.023	2.74***	7.44***
	[0.000]	[0.006]

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Table 14: Yearly stock returns and the interaction between volatility and stock performance

This Table presents Chow-type tests to examine the importance of operating performance for volatility. The dependent variable is the yearly stock return. Table 2 Panel B contains the variable definitions. The models also include year dummies and stock exchange dummies and cluster standard errors by firm. The important results are the tests to determine equality across coefficients A, B, C, and D (as indicated in the left hand side of the variables column). Brackets contain p-values and superscripts ***, **, and * denote significance at 1%, 5%, and 10%, respectively.

Dependent Variable	Yearly Stock Return			
Column	[1]	[2]	[3]	[4]
I(Operating Quintile 1)	-0.147***	-0.148***	-0.162***	
	[0.000]	[0.000]	[0.000]	
I(Operating Quintile 5)	0.064***	0.060***		0.090***
	[0.000]	[0.000]		[0.000]
I(Volatility Quintile 1)	0.029***		0.025***	0.037***
	[0.000]		[0.000]	[0.000]
I(Volatility Quintile 5)		-0.069***	-0.068***	-0.081***
		[0.000]	[0.000]	[0.000]
A: I(Volatility Quintile 1) x I(Operating Quintile 1)	0.015		0.009	
	[0.272]		[0.499]	
B: I(Volatility Quintile 1) x I(Operating Quintile 5)	-0.01			-0.021**
	[0.230]			[0.013]
C: I(Volatility Quintile 5) x I(Operating Quintile 1)		0.031***	0.029***	
		[0.000]	[0.000]	
D: I(Volatility Quintile 5) x I(Operating Quintile 5)		0.007		0.028***
		[0.539]		[0.007]
SMB	0.001	0.000	0.001	0.001
	[0.938]	[0.990]	[0.932]	[0.901]
HML	0.073***	0.072***	0.072***	0.069***
	[0.000]	[0.000]	[0.000]	[0.000]
Market Return	0.708***	0.706***	0.706***	0.710***
	[0.000]	[0.000]	[0.000]	[0.000]
ln(Assets)	0.010***	0.008***	0.007***	0.012***
	[0.000]	[0.000]	[0.000]	[0.000]
Tobin's Q	-0.006***	-0.006***	-0.006***	-0.006***
	[0.000]	[0.000]	[0.000]	[0.000]
Current Assets/ Current Liabilties	-0.001*	-0.001	-0.001	-0.002***
	[0.061]	[0.145]	[0.374]	[0.001]
I(Makes an Acquisition)	0.014***	0.013***	0.012***	0.019***
	[0.001]	[0.002]	[0.006]	[0.000]
Debt/Assets	-0.019*	-0.014	-0.037***	-0.015
	[0.083]	[0.205]	[0.001]	[0.194]
Intangibles/Assets	-0.143***	-0.139***	-0.139***	-0.151***
	[0.000]	[0.000]	[0.000]	[0.000]
CAPEX/Sales	-0.001	0.001	-0.002	-0.010***
	[0.854]	[0.768]	[0.596]	[0.002]
Constant	-0.597*	-0.144	-0.565	-0.842**
	[0.090]	[1.000]	[0.108]	[0.017]
Observations	134,945	134,946	134,945	134,945
Pseudo R-Squared	16.00%	16.10%	16.00%	15.30%
Wald Tests				
Test	A=B	C=D	A=C	B=D
F-Statistic	2.89*	4.63**	1.7	16.7***
p-value	[0.089]	[0.031]	[0.193]	[0.000]

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Table 15: The impact of volatility on stock returns for sub-samples based on operating performance improvements

This table contains results that split the sample by whether there is an operating performance improvement between year t-1 and year t. We define an improved firm as one whose operating performance quintile increases between year t-1 and year t. We analyze 'improving' firms in Columns 1-5; we analyze non-improving firms in Columns 6-10.

Sample	Operating Performance Improvement					No Operating Performance Improvement				
Dependent Variable	Yearly Stock Return					Yearly Stock Return				
Model	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
I(Volatility Quintile 1)	0.009					0.061***				
	[0.407]					[0.000]				
I(Volatility Quintile 2)		0.026***					0.028***			
		[0.003]					[0.000]			
I(Volatility Quintile 3)			0.029***					0.000		
			[0.001]					[0.974]		
I(Volatility Quintile 4)				-0.004					-0.030***	
				[0.637]					[0.000]	
I(Volatility Quintile 5)					-0.087***					-0.096***
					[0.000]					[0.000]
Spread: Small Less Big	0.015	0.014	0.015	0.015	0.015	-0.002	-0.002	-0.002	-0.001	-0.004
	[0.404]	[0.419]	[0.405]	[0.407]	[0.385]	[0.825]	[0.806]	[0.821]	[0.865]	[0.641]
Spread: High Less Low	0.139***	0.139***	0.139***	0.139***	0.140***	0.063***	0.062***	0.063***	0.063***	0.061***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Region Return	0.789***	0.788***	0.790***	0.789***	0.785***	0.714***	0.715***	0.718***	0.716***	0.707***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ln(Assets)	0.006**	0.005**	0.006**	0.006**	0.001	0.018***	0.020***	0.020***	0.020***	0.016***
	[0.014]	[0.029]	[0.012]	[0.010]	[0.512]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
EBIT/Assets	-0.006***	-0.006***	-0.006***	-0.006***	-0.006***	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Tobin's Q	-0.005***	-0.005***	-0.005***	-0.005***	-0.005**	0.001	0	0	0	0.001
	[0.007]	[0.006]	[0.007]	[0.006]	[0.014]	[0.468]	[0.573]	[0.559]	[0.615]	[0.164]
Current Assets/ Current Liabilities	0.023**	0.023**	0.023**	0.023**	0.020*	0.024***	0.025***	0.026***	0.025***	0.023***
	[0.031]	[0.037]	[0.033]	[0.031]	[0.066]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
I[Acquirer]	-0.053*	-0.050*	-0.051*	-0.053*	-0.043	-0.062***	-0.054***	-0.058***	-0.056***	-0.052***
	[0.071]	[0.088]	[0.079]	[0.072]	[0.139]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Debt/Assets	-0.169***	-0.167***	-0.169***	-0.169***	-0.158***	-0.150***	-0.156***	-0.158***	-0.156***	-0.143***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Intangibles/Assets	-0.042***	-0.041***	-0.042***	-0.042***	-0.036***	-0.016***	-0.018***	-0.018***	-0.018***	-0.010***
	[0.001]	[0.002]	[0.001]	[0.001]	[0.006]	[0.000]	[0.000]	[0.000]	[0.000]	[0.006]
CAPEX/Sales	0.855	0.861	0.834	-0.648	-1.187**	-0.332	1.136**	-0.348	-0.318	1.267***
	[1.000]	[1.000]	[1.000]	[0.264]	[0.040]	[1.000]	[0.021]	[1.000]	[1.000]	[0.010]
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock Exchange Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	23,703	23,703	23,703	23,704	23,704	91,991	91,992	91,991	91,991	91,992
R-squared	13.90%	13.90%	13.90%	13.90%	14.10%	15.50%	15.40%	15.30%	15.40%	15.70%

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Table 16: The impact of volatility on stock returns by whether there is a 'large' operating improvement

This table contains models that split the sample into sets of firms that experience a big operating improvement and those that do not. We define a 'big' improvement as shifting from operating performance quintile 1 or 2 in year t-1 to operating performance quintile 4 or 5 in year t.

Sample	Big Operating Performance Improvement					No Big Operating Performance Improvement				
Dependent Variable	Yearly Stock Return					Yearly Stock Return				
Model	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
I(Volatility Quintile 1)	-0.073*					0.052***				
	[0.085]					[0.000]				
I(Volatility Quintile 2)		0.029					0.026***			
		[0.372]					[0.000]			
I(Volatility Quintile 3)			0.022					0.006		
			[0.450]					[0.112]		
I(Volatility Quintile 4)				0.013					-0.023***	
				[0.637]					[0.000]	
I(Volatility Quintile 5)					-0.024					-0.095***
					[0.414]					[0.000]
Spread: Small Less Big	-0.02	-0.018	-0.018	-0.019	-0.018	0.002	0.001	0.002	0.002	0
	[0.726]	[0.746]	[0.749]	[0.739]	[0.752]	[0.841]	[0.863]	[0.838]	[0.825]	[0.999]
Spread: High Less Low	-0.031	-0.03	-0.029	-0.029	-0.03	0.075***	0.075***	0.075***	0.075***	0.074***
	[0.731]	[0.735]	[0.749]	[0.745]	[0.739]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Region Return	0.767***	0.775***	0.779***	0.776***	0.777***	0.725***	0.725***	0.727***	0.727***	0.718***
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
ln(Assets)	-0.006	-0.01	-0.01	-0.009	-0.011	0.016***	0.017***	0.018***	0.017***	0.014***
	[0.401]	[0.170]	[0.208]	[0.228]	[0.151]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
EBIT/Assets	-0.004*	-0.004*	-0.004*	-0.004*	-0.004*	-0.005***	-0.005***	-0.005***	-0.005***	-0.005***
	[0.069]	[0.073]	[0.072]	[0.067]	[0.069]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Tobin's Q	-0.012**	-0.012**	-0.012**	-0.012**	-0.012**	-0.001	-0.001	-0.001	-0.001	0
	[0.017]	[0.016]	[0.018]	[0.018]	[0.019]	[0.433]	[0.368]	[0.399]	[0.338]	[0.944]
Current Assets/ Current Liabilities	0.031	0.03	0.031	0.031	0.03	0.025***	0.025***	0.026***	0.026***	0.023***
	[0.364]	[0.382]	[0.369]	[0.372]	[0.388]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
I[Acquirer]	-0.078	-0.068	-0.071	-0.07	-0.065	-0.056***	-0.049***	-0.053***	-0.051***	-0.046***
	[0.389]	[0.452]	[0.430]	[0.440]	[0.471]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Debt/Assets	-0.302***	-0.302***	-0.302***	-0.304***	-0.302***	-0.147***	-0.152***	-0.153***	-0.153***	-0.140***
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Intangibles/Assets	-0.057	-0.055	-0.056	-0.056	-0.055	-0.020***	-0.021***	-0.022***	-0.022***	-0.014***
	[0.326]	[0.345]	[0.336]	[0.336]	[0.338]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
CAPEX/Sales	-0.515	-0.483	-0.51	-0.492	-0.464	-0.797***	-1.889	1.054**	1.059**	-0.263
	[0.585]	[0.608]	[0.589]	[0.602]	[0.623]	[0.005]	[1.000]	[0.046]	[0.045]	[1.000]
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Stock Exchange Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,335	3,335	3,335	3,335	3,335	112,360	112,363	112,362	112,362	112,361
R-squared	12.70%	12.70%	12.70%	12.70%	12.70%	15.00%	14.90%	14.90%	14.90%	15.20%

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