Profitability Anomaly and Aggregate Volatility Risk

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Abstract

Firms with lower profitability have lower expected returns because such firms perform better than expected when market volatility increases. The better-than-expected performance arises because unprofitable firms are distressed and volatile, their equity resembles a call option on the assets, and call options value increases with volatility, all else fixed. Consistent with this hypothesis, the profitability anomaly and its exposure to aggregate volatility risk are stronger for distressed and volatile firms; for such firms, aggregate volatility risk explains roughly half of the profitability anomaly, while in single sorts on profitability about 70% of the anomaly is explained.

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1 Introduction

Profitability has been known since at least Haugen and Baker (1996) to positively predict returns in cross-section. In recent years, the profitability anomaly has gained more prominence and several papers (Fama and French, 2015, Chen, Novy-Marx, and Zhang, 2011, Hou, Xue, and Zhang, 2015) have suggested using the high-minus-low profitability factor in addition to, or as a replacement of, the traditional size and value factors (SMB and HML) of Fama and French (1993).

While the relation between profitability and expected returns seems strong and the factor models augmented with the profitability factor (RMW) look capable of explaining a long list of anomalies the Fama-French (1993) and Carhart (1997) models could not explain, the economic mechanism that leads to profitability being priced is still unclear. The literature presents compelling reasons of why profitability should proxy for risk, but remains agnostic about a particular risk it picks up. For example, Hou, Xue, and Zhang (2015) argue that high-risk firms have a high required rate of return and thus will only implement highly profitable projects, whereas low-risk firms have a lower threshold for investment projects and will also implement low-profitable projects. This argument, however, does not tell us which state variable profitable and unprofitable firms covary with and how and when the high risk of most profitable firms is realized. Do these firms lose more than expected when GDP growth stalls? Does their risk go up in periods of high unemployment? Is the magnitude of the risk picked up by profitability enough to explain the return spread we observe in the profitability sorts? The answer the literature is currently giving is "we do not know".

Even more, as Ohlson (1995) and Kothari (2001) show, the positive relation between expected profitability and expected return (controlling for investment and market-to-book) follows directly from the juxtaposition of the dividend discount model and clean surplus accounting. This derivation of the profitability anomaly makes it impossible to distinguish between rational and irrational explanations: the price the dividend discount model comes up with can be irrational if expectations of profitability used in the model are irrational, but the positive relation between expected profitability and expected return will remain intact in this case as well, because this relation just follows from an accounting identity.

This paper presents the first attempt to highlight a particular risk source behind the profitability anomaly. The main contribution of the paper is the finding that unprofitable firms perform abnormally well when expected market volatility (proxied by the VIX index) increases, and highly profitable firms perform unexpectedly poorly in the same periods, as indicated by their loadings on a factor-mimicking portfolio, FVIX, that tracks daily changes in VIX.[1] In the full sample, augmenting standard factor models with FVIX reduces by 50-70% the alpha of RMW and the alphas of similar high-minus-low profitability strategies that buy/short firms in the top/bottom profitability quintile. Even in the subsamples where the profitability anomaly is the strongest (distressed/volatile firms), FVIX explains at least (one-third) one-half of the (gross) profitability anomaly.

The economic mechanism that links profitability to aggregate volatility risk works through convexity in the equity value introduced by limited liability. As Merton (1974) points out, equity can be thought of as a call option on the assets with the strike price equal to the value of debt. For financially healthy firms though, this option is so deeply in

[1] I use older version of VIX, which currently has ticker VXO. The current VIX index was introduced in 2003 and then the data were backfilled to 1990. Both versions of VIX are not tradable, hence the need to do the factor-mimicking regression; data on tradable volatility positions like straddles start in 1996 or later. Section 3.2 of online Robustness Appendix shows that results in the paper stay similar if the current version of VIX is used.

the money that the convexity it creates in the equity value is minimal. Unprofitable firms, however, tend to be distressed and thus their equity has significant amount of convexity.[2] The convexity comes in handy in recessions, when both the market as a whole and the firm itself become quite volatile:[3] as any option, the equity of unprofitable firms performs well, all else equal, when the assets become more volatile. Because of limited liability, higher volatility is preferable for shareholders of a firm close to bankruptcy, as they have a claim on potential gains, but potential losses are likely to fall on debtholders' shoulders.[4]

The argument can also be turned around to predict that the most profitable firms underperform when market volatility increases and thus are exposed to aggregate volatility risk. Indeed, if equity of the most profitable firms is thought of as a call option on the assets, this option is the furthest in the money, and thus the most profitable firms have less convexity to their equity value than an average firm, benefit the least from increases in market volatility, and therefore, all else equal, perform worse than an average firm (with similar market beta) in volatile periods.

As Campbell (1993) and Chen (2002) show, good performance in response to increases

[2]In the options literature, this result is known as vega (option's value derivative with respect to volatility) reaching its maximum when the option is exactly at the money. While equity of extremely distressed/unprofitable firms can be out the money (with debt being greater than the value of assets the firm has), and such firms will have lower vega than "at the money" firms, such firms are unlikely to be numerous: as Table 1 reports, the median firm in the bottom profitability quintile still has leverage (debt over firm value) of 25%, credit rating of Ba3, and expected default probability of 3.3%.

[3]See, e.g., Barinov, 2013, Duarte et al., 2012, and Herskovic et al., 2016, for evidence that market volatility and average/median idiosyncratic volatility tend to increase simultaneously, and the increase tends to happen during recessions.

[4]Theory Appendix at https://www.dropbox.com/s/kfq0ernp1kousps/Theory%20Appendix%20blind.pdf?dl=0 presents a formal model that extends the model in Johnson (2004), in which equity is a call option on the assets and the value of assets is observed with an error. The model in Theory Appendix shows that higher uncertainty about the value of the assets (generated by the error) makes the market beta of equity smaller and particularly so in recessions, and for this reason, as well as because options are more valuable in a volatile environment typical of recessions, levered firms are a hedge against aggregate volatility risk. The uncertainty parameter in the model is monotonically related to idiosyncratic volatility of equity returns, and based on the tight correlation between profitability and leverage/distress in the data, in this paper I predict that profitability is positively related to aggregate volatility risk exposure and thus to expected returns, and this effect is stronger in the high idiosyncratic volatility subsample.

in aggregate/market volatility is desirable and warrants lower risk premium. In the Intertemporal CAPM (ICAPM) with stochastic volatility, Campbell shows that higher aggregate volatility indicates worse times ahead, and thus triggers higher savings and lower consumption, and Chen argues that higher aggregate volatility additionally triggers precautionary savings, with the same consequence of endogenous consumption drop. Assets that alleviate this consumption drop by posting relatively good return are valuable hedges.

The caveat about the mechanism above is that it does not imply that low profitability firms gain in volatile periods of time or that the high-minus-low profitability strategy necessarily loses money when aggregate volatility increases. Low profitability firms, being distressed and option-like, have higher market betas than stable and highly profitable firms, and when market volatility increases and market simultaneously drops[5], these firms are likely to lose value, and the high-minus-low profitability strategy is likely to gain.

The volatility risk explanation of the profitability anomaly argues, however, that the losses of low profitability firms in periods of increasing aggregate volatility will be much smaller than what their market beta suggests. Thus, the CAPM (as well as other standard factor models) overestimates the risk of unprofitable firms and concludes that these firms have too low returns for their level of risk (i.e., they have negative alphas). Likewise, standard factor models underestimate the risk of the high-minus-low profitability strategy, which does not gain nearly as much (or possibly does not gain at all) during volatile periods. This mis-estimation is corrected by controlling for aggregate volatility risk, which makes the respective alphas disappear.[6]

[5] In 1986-2014, the correlation between daily market returns and VIX changes was -0.704.

[6] Campbell et al. (2008) briefly considered VIX as an explanation of negative alphas earned by distressed firms and concluded that such explanation is unlikely, since distressed firms tend to do badly when VIX increases. The argument in this paragraph and the paragraph before explains why such conclusion would be premature: to earn a negative alpha because of a missing risk factor, during recessions a firm does not have to gain, it just has to perform better than an average firm with the same market beta. When

After Section 2 provides a review of related papers and Section 3 describes the data, the empirical tests proceed as follows. In Section 4, I start with confirming that profitability is negatively related to distress. I also document that firms with lower profitability have higher firm-specific volatility, which is not surprising given the levered nature of unprofitable/distressed firms, and will be useful later in studying the cross-section of the profitability anomaly. Lastly, I find that profitability is positively related to growth options, so the value of unprofitable firms is likely to be convex because they are distressed, but unlikely to be convex because unprofitable firms tend to have few growth options. On the balance though, as overall measures of firm convexity developed by Grullon et al. (2012) suggest, unprofitable firms have more convexity than profitable ones.

Section 5 then proceeds to show that my aggregate volatility factor, FVIX, which tracks changes in the VIX index, can explain the Fama-French profitability factor, but not the other way around. FVIX also explains the alphas of profitability-sorted quintile portfolios, as well as the high-minus-low alpha spread, by revealing the hedging ability of unprofitable firms against aggregate volatility risk and the significant exposure of highly profitable firms to this risk.

The conclusion that aggregate volatility risk explains the profitability anomaly is further supported under a different research design. Firm-level Fama-MacBeth (1973) regressions reveal that historical return sensitivity to VIX changes (an alternative measure of aggregate volatility risk) subsumes profitability and gross profitability, thus also explaining the related gross profitability anomaly of Novy-Marx (2013).

The aggregate volatility risk explanation of the profitability anomaly suggests that profitability picks up equity convexity stemming from distress. An obvious hypothesis is

VIX increases and the market drops, unprofitable firms lose, but they lose less than firms with the same market beta, which makes them risky, but less risky than what the CAPM suggests.

that the profitability anomaly should be driven exclusively by distressed firms, for which sorting on profitability will produce the widest spread in convexity, expected returns, and volatility risk. Section 6 successfully tests this hypothesis and finds that the profitability anomaly is indeed concentrated exclusively in the top distress quintile. Likewise, the FVIX beta of the high-minus-low profitability strategy is the largest in the top distress quintile, thus largely explaining the variation of the profitability anomaly with distress. In the top distress quintile, FVIX can explain between 35% and 75% of the profitability anomaly depending on profitability measure used.

The aggregate volatility risk explanation of the profitability anomaly also relies on a significant presence of idiosyncratic volatility. When aggregate volatility increases, idiosyncratic volatility also rises, thus benefiting the convex equity value of unprofitable/distressed firms. In order for this channel to work, idiosyncratic volatility has to be sufficiently high, because an increase from tiny to very small idiosyncratic volatility is unlikely to affect the value of equity much. The cross-sectional prediction is then that the profitability anomaly is stronger for high idiosyncratic volatility firms and that FVIX will be able to explain why this is the case.

This is largely what Section 6 finds: the profitability anomaly comes entirely from the top idiosyncratic volatility quintile, and this is also the only quintile in which the high-minus-low profitability strategy is significantly exposed to aggregate volatility risk. The differential in FVIX exposure explains roughly one-half of the difference in the profitability anomaly between high and low volatility subsamples and 40-50% of the profitability anomaly for high idiosyncratic volatility firms.

Section 7 looks at recent work by Ball et al. (2015, 2016, 2019) who suggest alternative profitability measures and finds that FVIX largely explains the profitability anomaly those measures generate. Section 7 also presents direct evidence that, when VIX increases, the high-minus-low profitability strategies have negative alphas and unprofitable firms have positive alphas. Section 8 summarizes additional tests performed in online Robustness Appendix and Section 9 concludes.

2 Related Literature

Two recent theoretical papers use a mechanism similar to the one in this paper to explain the profitability anomaly. Hackbarth and Johnson (2015) present a model with both operating leverage and growth options and find that the relation between profitability and expected returns is largely positive, but is best approximated by a third-degree polynomial. The relation is strictly positive for sufficiently high levels of profitability (higher profitability makes risky growth options take a larger fraction of the firm) and for sufficiently low levels of profitability (lower profitability makes the contraction option, which is a hedge, take a larger fraction of the firm). Hackbarth and Johnson model is set up in a one-factor world, so in the model Conditional CAPM should explain the profitability premium, and thus Hackbarth and Johnson do not suggest adding an extra factor (though they do remark that in heterogenous simulated panels firm characteristics like profitability and investment have explanatory power beyond the market beta).

The mechanism in this paper focuses on a different type of convexity in the firm value (equity of a levered firm being an option on the assets), but it would also predict that the market beta of unprofitable firms is procyclical (e.g., Johnson, 2004, shows that the beta of the call option created by leverage decreases in volatility, and both systematic and idiosyncratic volatility decrease in recessions as described above). My paper goes further and suggests using market volatility as a state variable, which should also encompass the conditional market beta effects. In online Robustness Appendix,[7] I show that, consistent with Hackbarth and Johnson (2015), Conditional CAPM empirically explains about one-third of the profitability anomaly, leaving the rest statistically and economically significant. I also find that FVIX betas of high-minus-low profitability portfolios decline by about one-third, but stay highly significant if the market beta is made conditional, and making the market beta conditional in the two-factor model with the market factor and FVIX does not materially change the alphas of the high-minus-low profitability portfolios.

McQuade (2018) uses volatility risk to explain low expected returns to distressed firms. The intuition in the model is similar to mine: distress makes the option to default more important, since any option's value increases with volatility, all else equal, and thus distressed firms are hedges against volatility risk. My paper shows that profitability is strongly related to distress, and thus one can view it as an empirical test of McQuade (2018).

On the other hand, McQuade solves his model using asymptotic expansions, and this technical method requires the assumption that it is long-run shocks to volatility that explain the low expected returns to distressed firms. The state variable I use is VIX, which is implied volatility of one-month options on the market, i.e., short-run volatility. So, this paper and McQuade (2018) disagree on what part of market volatility (short-run or long-run) matters. In online Robustness Appendix, I follow Adrian and Rosenberg (2008) and divide Component GARCH forecast of market volatility into the short-run component (that mean-reverts fast) and long-run component (that mean-reverts extremely slowly). I find that returns to the high-minus-low profitability portfolios are negatively related to innovations in short-run volatility (just as they are negatively related to FVIX), but unrelated or positively related to innovations in long-run volatility. I also find that the

[7] Available at https://www.dropbox.com/s/hjiz2otrk5bkbd3/Robustness%20Profitability%20blind.pdf?dl=0

three-factor ICAPM with the market factor and two factor-mimicking portfolios for innovations to short-run and long-run expected volatility produces mostly significant estimates of the profitability anomaly, twice larger than those from the two-factor ICAPM with market and FVIX. If the short-run volatility factor and FVIX are used together to explain the profitability anomaly, they demonstrate a strong overlap, with either one or the other becoming insignificant depending on the profitability measure, but the alphas of the high-minus-low profitability portfolios show no improvement over those from the two-factor ICAPM with the market and FVIX, which suggests that the short-run volatility factor is a weaker version of FVIX.

Several recent papers look at the relation between growth options, volatility, and expected returns. Lyle (2019) uses the argument similar to Johnson (2004) to predict that firms with low information quality (and high idiosyncratic volatility) can have low, not high expected returns if they have abundant growth options. Barinov and Chabakauri (2022) argue that volatility risk can explain the value premium, as growth firms are option-like and therefore hedges against volatility risk.

Section 4 of the paper shows that sorts of profitability create an inverse sort of growth options, and thus the link between growth options and volatility risk found by Barinov and Chabakauri (2022) works against finding a similar link between profitability and volatility risk. Additionally, Barinov and Chabakauri find that the value premium is explained mostly by exposure to changes in average idiosyncratic volatility rather than changes in aggregate volatility, and Lyle (2019) limits his analysis to finding the cross-sectional link between growth options and the effect of information quality on expected returns, without attributing the link to aggregate volatility risk.

3 Data

The main variable of the study, profitability, is defined in two alternative ways: first, following most studies, as net income before extraordinary items (Compustat annual ib item) divided by book value of equity (ceq plus txdb), second, following Novy-Marx (2013), as total revenue (sale) minus cost of goods sold (cogs) divided by book value of equity (in which case it is referred to as gross profitability). Firms are given six months to announce their annual financials, that is, in December 1991 it is assumed that the market knows profitability of firms with fiscal year ends in June 1991 or earlier.

The portfolio sorts in the paper use NYSE (exchcd=1) breakpoints. Stocks with prices below $5 on the portfolio formation date are excluded. The results in the paper are robust to using CRSP breakpoints and/or including the stocks priced below $5 back into the sample.

In all tests, I use monthly cum-dividend returns from CRSP and complement them by the delisting returns from the CRSP events file. Following Shumway (1997) and Shumway and Warther (1999), I set delisting returns to -30% for NYSE and AMEX firms (CRSP `exchcd` codes equal to 1, 2, 11, or 22) and to -55% for NASDAQ firms (CRSP `exchcd` codes equal to 3 or 33) if CRSP reports missing or zero delisting returns and delisting is for performance reasons. My results are robust to setting missing delisting returns to -100% or to using no correction for the delisting bias.

To measure the innovations to expected aggregate volatility, I use daily changes in the old version of the VIX index calculated by CBOE and available from WRDS. Using the old version of VIX (current ticker VXO) provides longer coverage. The VIX index measures the implied volatility of the at-the-money options on the S&P100 index.

I form a factor-mimicking portfolio that tracks the daily changes in the VIX index. I regress daily changes in VIX on daily excess returns to the base assets.[8] The base assets are five quintile portfolios sorted on past return sensitivity to VIX changes, as in Ang et al. (2006):

$$\begin{aligned}\Delta VIX_t \;=\; & \underset{(0.020)}{0.059} - \underset{(0.076)}{0.027} \cdot (VIX1_t - RF_t) - \underset{(0.157)}{0.657} \cdot (VIX2_t - RF_t) - \underset{(0.113)}{0.350} \cdot (VIX3_t - RF_t) \\ & - \underset{(0.392)}{0.656} \cdot (VIX4_t - RF_t) + \underset{(0.140)}{0.162} \cdot (VIX5_t - RF_t), \quad R^2 = 0.505 \end{aligned} \tag{1}$$

where $VIX1_t, \ldots, VIX5_t$ are value-weighted VIX sensitivity quintiles described below, with $VIX1_t$ being the quintile with the most negative sensitivity, and the numbers in brackets below the coefficients are standard errors. The fitted part of the regression above less the constant is my aggregate volatility risk factor (FVIX factor). The daily returns to FVIX are then cumulated to the monthly level.

The R-square of the factor-mimicking regression implies that the correlation between FVIX and ΔVIX is at 0.71, indicating that FVIX does a good job tracking the state variable it is designed to track (ΔVIX).

The return sensitivity to VIX changes ($\gamma_{\Delta VIX}$) I use to form the base assets is measured separately for each firm-month by regressing daily stock excess returns in the past month on daily market excess returns and the VIX index change using daily data (at least 15 non-missing returns are required):[9]

$$Ret_t - RF_t = \alpha + \beta_{MKT} \cdot (MKT_t - RF_t) + \gamma_{\Delta VIX} \cdot \Delta VIX_t. \tag{2}$$

[8]The factor-mimicking regression is performed using the full sample to increase the precision of the estimates. In Section 8.5, I find that all results in the paper are robust to using an out-of-sample version of FVIX that is estimated using expanding window.

[9]Following Ang et al. (2006) and other papers that use FVIX (e.g., Barinov, 2013, Barinov and Chabakauri, 2022), I do not exclude stocks priced below $5 at the portfolio formation date from the base assets when I form FVIX (while those stocks are later excluded from profitability portfolios. The results in the paper are robust to using FVIX purged of low-priced stocks.

By construction, FVIX is the portfolio that tends to earn positive returns when expected market volatility increases, and hence FVIX is a hedge against aggregate volatility risk. Therefore, when FVIX is used in factor models, a negative FVIX beta indicates exposure to aggregate volatility risk, and portfolios with positive FVIX betas are deemed hedges against volatility risk.

The sample in the paper is driven by VIX availability and goes from January 1986 to December 2014. All other variables used in the paper are described in the Data Appendix.[10]

4 Descriptive Statistics

Table 1 presents median values of distress measures and firm-specific volatility measures across profitability quintiles. The main goal of Table 1 is to confirm that low profitability firms are option-like and volatile, since that would imply, according to my explanation of the profitability anomaly, that low profitability firms are hedges against increases in aggregate volatility, thus explaining their negative alphas, and high profitability firms, lacking either volatility or option-likeness, are the least likely to offer a hedge against aggregate volatility risk.

Panel A looks at the median values of a variety of distress measures across profitability quintiles. The overall conclusion from Panel A is that all distress measures are twice higher in the lowest profitability quintile, and the difference between the lowest and highest profitability quintiles is always statistically significant. For example, market leverage changes from 0.102 to 0.253 as one goes from highly profitable to highly unprofitable firms, and median credit rating goes down five grades from A- to BB.

Higher firm-specific volatility of less profitable firms is another necessary condition for

[10]Available at https://www.dropbox.com/s/506dblsmw5p7lty/Data%20Appendix%20Profitability.pdf?dl=0

the volatility risk explanation of the profitability anomaly. While more option-like (e.g., distressed) firms react more positively, all else equal, to increases in aggregate volatility and simultaneous increases in firm-specific volatility, for low volatility firms this positive effect is unlikely to be strong, as their volatility will likely increase from very small to small (see Barinov, 2017, for supporting empirical evidence).

Panel B looks at measures of firm-specific volatility across profitability quintiles and finds a similarly strong inverse relation between profitability and volatility, with an upward spike in the bottom profitability quintile (the spike is expected due to equity value convexity of distressed firms). Panel B thus shows that unprofitable firms are not only more option-like (see Panel A, as well as Panel D discussed below), but also more volatile than profitable firms. Hence, unprofitable firms are likely to beat the CAPM when aggregate volatility unexpectedly increases (i.e., load positively on the volatility risk factor), and the reverse should be true about profitable firms, with their low volatility and little option-likeness.

Panel C looks at growth options measures across profitability sorts. Several recent papers (Ai and Kiku, 2013, Barinov and Chabakauri, 2022, McQuade, 2018) suggest that volatility risk may explain the value premium. Panel C of Table 1, however, shows that this explanation is unlikely to carry over mechanically to profitability sorts, since in the data it is high profitability firms that seem to have abundant growth options: compared to low profitability firms, high profitability firms have twice higher market-to-book and investment-to-assets ratios, three times higher investment growth and 40% higher sales growth. Future sales growth, which can be viewed as a measure of growth options exercised in the future, is also twice higher in the highest profitability quintile. Thus, the relation between growth options and volatility risk discovered by the aforementioned papers would imply that it is high, not low profitability firms that are hedges against volatility risk. In contrast to the aforementioned papers, this paper focuses on the other dimension of firm convexity, created by distress and leverage and related to volatility risk, and the relation between profitability and growth options in Panel C works against me.

Panel D uses two catch-all measures of firm convexity suggested by Grullon et al. (2012). The first measure, SUE flex, looks at the non-linearity of SUE-return relation by regressing earnings announcement return on SUE and SUE squared. SUE flex is the slope on the quadratic term in this regression. The second measure, TVol sens, is a measure that regresses firm returns directly on the market return and change in the firm's total volatility, with the positive slope implying convexity.

Panel D shows that the negative relation between profitability and distress (Panel A) trumps the positive relation between profitability and growth options (Panel C), and low profitability firms come across as more convex according to both catch-all convexity measures. Higher convexity of low profitability firms in turn suggests that those firms will be hedges against volatility risk and thus volatility risk will explain their low returns and the resulting profitability anomaly.

5 Explaining the Profitability Anomaly

5.1 Preliminary Evidence from the Great Recession

The main prediction of the paper is that unprofitable firms, due to convexity in equity value introduced by limited liability, will perform abnormally well when volatility increases in recessions, and profitable firms will be on the other side of the spectrum and will perform poorly. This prediction is true "holding everything else fixed": both profitable and unprofitable firms have positive market betas and will lose value in a recession, but my prediction is that unprofitable firms will lose less than expected and vice versa.

Figure 1 provides the first illustration of that by looking at how the bottom profitability quintile and the high-minus-low profitability portfolio (long in the top quintile, short in the bottom quintile) perform between September 2007, when the subprime mortgage crisis started, and June 2009, which marked the start of economic recovery according to NBER.

Figure 1A (1C) plots cumulative returns to the bottom (gross) profitability quintile, along with expected return to that quintile from the CAPM equation and cumulative market return. One can observe that despite having betas exceeding unity (1.3 and 1.15, respectively) firms in the bottom (gross) profitability quintile perform on par with, and sometimes better than the market portfolio, while the high betas should make them trail the market when the market is heading down. Thus, cumulative returns to the bottom (gross) profitability quintile are consistently above the CAPM expectation, and the gap only widens in the second half of the graph, after the Lehman collapse in September 2008 and subsequent market crash.

Figure 1B (1D) plots the ratio of cumulative returns of the top and bottom (gross) profitability quintile, which essentially represents the profitability anomaly. Since firms in the top (gross) profitability quintile have beta of (0.88) 0.92, it is expected that the ratio will be growing when the market is falling. Figures 1B and 1D, however, find that during the Great Recession the ratio was growing slower than the CAPM would predict, consistent with my prediction that unprofitable firms outperform in recessions and vice versa.

The degree of unexpected performance depicted in Figure 1 is economically sizeable: Figures 1A and 1C suggest that a market-neutral position that shorts unprofitable firms (chasing their negative alpha) and invests the appropriate amount in the market portfolio to keep the beta zero, over the course of the Great Recession would set the investor back by roughly 10%. Figures 1B and 1D add that the market-neutral version of the high-minus-low profitability portfolio would underperform, during the same period, by the total of 15-20%.

While illustrative, Figure 1 presents an isolated episode of unprofitable firms outperforming in bad times. A proper way of establishing that, controlling for market beta, unprofitable firms do well and profitable firms do poorly when volatility increases is to control for the market return in a multiple regression with one of the profitability quintiles or the high-minus-low profitability portfolio as the dependent variable and the market factor and FVIX as regressors. A positive FVIX beta in such regression would mean that a market-neutral position in the asset on the left-hand side would gain when VIX increases, and vice versa.[11] This is the approach that will be followed in the rest of the paper.

5.2 RMW Factor and Aggregate Volatility Risk

Fama and French (2015, 2016) suggest replacing the three factor Fama-French (1993) model with a new five-factor model, which adds an investment factor (CMA) and profitability factor (RMW) to the existing three (market, SMB, and HML). Several other papers (Hou, Xue, and Zhang, 2015, Chen, Novy-Marx, and Zhang, 2011) promote alternative factor models with a similar profitability factor, while Ball, Sadka, and Sadka (2009) suggest using economy-wide average profitability as a state variable in the ICAPM setting.

The new Fama and French profitability factor (RMW, robust-minus-weak) is a long-short portfolio that buys (shorts) firms that fall into the top (bottom) 30% in terms of profitability. In order to eliminate any confounding size effects, Fama and French sort all

[11]The market-neutral position can be easily formed by investing a certain sum in the asset on the left-hand side and shorting the market for that sum times the market beta from the regression (or buying the market if the beta is negative).

firms independently on size and profitability and follow the high-minus-low profitability strategy separately in the large firms and small firms subsample (large and small firms are separated using NYSE median market cap as the cut-off). While the returns of the high-minus-low profitability strategy are value-weighted in the large and small firms subsamples, RMW represents simple average of these returns.

Table 2 starts with reporting descriptive statistics of the five Fama-French factors and FVIX in Panel A. Before risk-adjustment, FVIX seems to have by far the largest factor risk premium, but it also has by far the largest volatility, and its CAPM alpha is only third in absolute magnitude among the factors. The Sharpe ratio and the appraisal ratio of FVIX are still the highest in absolute magnitude, but the gap between them and the next best ones is not extreme.

RMW, on the other hand, has medium-sized average return, but rather low volatility – so after risk-adjustment its CAPM alpha becomes close in size to that of FVIX, and its appraisal ratio comes in second after the appraisal ratio of FVIX. Another similarity between FVIX and RMW is relatively large skewness (positive for positive-alpha RMW, negative for negative-alpha FVIX).

Next, Table 2 performs a horse race between RMW and FVIX by regressing RMW returns on several commonly used asset-pricing factors with and without FVIX in Panel B and then flipping the regressions over in Panel C and regressing FVIX on the same asset-pricing factors with and without RMW.

Panel B reveals that the profitability factor retains significant alphas in all standard asset pricing models, but adding FVIX to any of them reduces the alphas to statistically insignificant values of 12-18 bp per month. In particular, the raw return of RMW is at 36 bp per month, the CAPM alpha is at 48 bp per month, t-statistic 3.35, and the Carhart

(1997) alpha is at 37 bp per month, t-statistic 2.84. Adding FVIX to the CAPM (Carhart model) reduces the alpha of RMW to 11.9 (13.4) bp per month, t-statistic 0.70 (1.13).

Turning to the betas of RMW with respect to other factors, I find, most importantly, that FVIX betas of RMW are large and significantly negative no matter what model FVIX is added to. The negative FVIX betas suggest that the short side of RMW (unprofitable firms) is likely to be a hedge against aggregate volatility risk, and the long side of FVIX (highly profitable firms) is likely to be exposed to aggregate volatility risk, just as my explanation of the profitability anomaly suggests. The fact that the alpha of RMW disappears after I control for FVIX further suggests that the volatility risk explanation is sufficient to explain the profitability anomaly.

I also find that the momentum beta of RMW is insignificant, which is interesting, because one would suspect that sorting on past earnings would partly capture earnings momentum. The momentum beta of RMW, while slightly positive, suggests that the overlap between earnings momentum and the profitability anomaly is minor.

In Panel C, I run FVIX on standard asset-pricing factors, including the new Fama-French factors, RMW and CMA. First, I find that the alpha of FVIX in standard models is significantly negative. The average raw return to FVIX is -1.34% per month, and the CAPM, Fama-French, and Carhart alphas vary in a tight range between -45 and -47 bp per month, with t-statistics well above 3 in absolute magnitude.

The negative sign of FVIX alpha is expected. By construction, FVIX tends to earn positive returns when market volatility increases, and thus represents an insurance against volatility increases. The negative alpha of FVIX is the insurance premium investors are willing to pay, and the fact that it is large and significant confirms that FVIX is a valid risk factor.

Also, the fact that FVIX alphas are similar in the CAPM, Fama-French model, and Carhart model suggests that FVIX has little overlap with standard asset-pricing factors and is unlikely to pick up the factor structure that they capture.

Adding the new factors, RMW and CMA, to either the Fama-French or Carhart model diminishes the FVIX alpha by about 15 bp per month, if both RMW and CMA are controlled for, and by 8-9 bp, if one controls for RMW only, and leaves the FVIX alpha economically large at roughly -30 bp per month and statistically significant with t-statistics above 3.5 by absolute magnitude. Juxtaposing this result with Panel B, in which FVIX reduces RMW alphas to almost zero, I conclude that while FVIX can explain RMW, RMW cannot explain FVIX.

The results in Panels B and C can be interpreted in the spirit of spanning tests in Barillas and Shanken (2017) and Fama and French (2018). Barillas and Shanken argue that the only thing that matters for comparison of two factor models is whether the factors of one model can explain the factors of the other model. In Table 2, my goal is smaller: I do not argue that the two-factor ICAPM with the market factor and FVIX can replace the Fama and French (2015) five-factor model. Table 2 shows that even if the investor trades the five factors from Fama and French (2015) and the momentum factor, adding FVIX improves the investment opportunity set. However, if the investor trades the market factor and FVIX (and potentially, though not necessarily, some other factors), adding RMW does not improve the maximum Sharpe ratio the investor can achieve. Hence, FVIX is likely to be the fundamental phenomenon (volatility risk), and RMW a particular manifestation of this phenomenon.

As Panel C finds, FVIX has a large and negative average return and significantly negative alphas. Panel D presents direct evidence that FVIX indeed serves as an insurance against volatility increases by reporting FVIX average return and FVIX alphas estimated in the months when VIX increases by 4 (5, 6, etc.) or more points, as indicated by the first column of Panel D.[12]

Since FVIX is constructed to be positively correlated with VIX changes, it is not surprising that in the months when VIX jumps up by 4 points or more, average return to FVIX stands at 6.72%. In more extreme months, average return of FVIX is even higher (e.g., in the months when VIX jumps up by 6 points or more, FVIX average return is 11.2%).

A large part of these large average returns is due to the fact that FVIX has a large and negative market beta. In the next columns of Panel D, I look at the CAPM, Carhart (1997), and five-factor Fama and French (2015) alphas of FVIX estimated in subperiods when VIX sharply increases. Since the sample size is relatively small (e.g., my sample has only 34 months with VIX increase exceeding 5 points), the alphas are often not statistically significant, but they are economically large and predominantly positive irrespective of the model used (in sharp contrast to the significantly negative alphas FVIX has in the full sample, see Panel C). For example, in the months when VIX increases by more than 5 (6, 7) points, the five-factor alpha of FVIX is 0.85% (1.60%, 1.66%) per month, t-statistic 2.11 (1.69, 1.34).

I conclude from Panel D that FVIX indeed provides good insurance against VIX increases: during months when VIX increases significantly, FVIX posts large positive returns and appears to have positive alphas.

[12]Months with large VIX increases tend to be months when market sharply drops: e.g., the average excess market return in months when VIX increases by 5 or more points is -6.37%, and only 3 out of 34 such months have a positive market return. The probability of NBER-defined recession in months of $\Delta VIX > 5$ is also twice higher than in an average month; some months with extremely large VIX jumps are also months when the economy barely dodged a recession (October 1987, August 1998, July-September 2011) or when a recession was already in the cards (July 2007, November 2007).

5.3 Aggregate Volatility Risk across Profitability Quintiles

Table 3 looks deeper into the profitability anomaly and reports alphas and FVIX betas for all profitability quintiles. The quintiles are formed using NYSE (exchcd=1) breakpoints and exclude stocks priced below $5 at the portfolio formation date.[13] Panels A1 and A2 sort firms on profitability (net income before extraordinary items over book value of equity), Panels B1 and B2 follow Novy-Marx (2013) and sort on gross profitability (sales less COGS over book value of equity).

The top row of Panel A uses the CAPM as the benchmark and estimate the (gross) profitability anomaly at 56.6 (46.9) bp per month, t-statistic 2.44 (2.48). The CAPM alphas increase steadily as one goes from low to high profitability firms, and the profitability anomaly comes primarily from the short side, which is the focus of my hypothesis. In the Carhart alphas, the (gross) profitability anomaly is very similar, but the momentum factor makes the alpha of low profitability firms smaller, since they tend to be recent losers.[14]

The next row in Panel A presents the alphas from the two-factor ICAPM with the market factor and FVIX and shows that controlling for FVIX explains the profitability anomaly. The high-minus-low alpha spread is reduced to 0.0 bp per month in Panel A1 and to only 12.0 bp per month in Panel B. The alphas of almost all quintiles, including the extremes that have significant CAPM alphas, are within 18 bp from zero and statistically insignificant. The alphas from the five-factor model (the Carhart model augmented with FVIX) in the second row of Panel B are qualitatively similar.

The last row in Panels A and B reports FVIX betas and reveals that, consistent with

[13]In untabulated findings, I find that the results stay similar if I use CRSP breakpoints and/or include stocks priced below $5 back into the sample.

[14]FVIX can contribute to explaining the negative alphas of losers as well, and Table 4 below suggests a 25% overlap between FVIX and the momentum factor, so the weak significance of Carhart alphas of unprofitable firms is consistent with my explanation of the profitability anomaly.

my hypothesis, unprofitable firms have significantly positive FVIX betas (indicating their superior performance during periods of increasing aggregate volatility) and profitable firms have significantly negative FVIX betas (indicating their inferior performance in such periods due to the lack of convexity in their equity value compared to an average firm). The FVIX betas decrease monotonically across profitability quintiles, and their high-minus-low differential of -0.843, t-statistic -3.30, in Panel A1, for example, is economically sizeable given the alpha of FVIX of roughly -45 bp per month (see Panel B of Table 2).

In untabulated results, I also add the investment factor (CMA) and the Pastor and Stambaugh (2003) liquidity risk factor to the Carhart model and the Carhart model augmented with FVIX and find that the results are very similar to the ones in Table 3.

In online Robustness Appendix,[15] I also verify that during recessions unprofitable firms beat profitable firms on non-price-related measures: unprofitable firms experience in recessions the same increase in frequency of credit rating downgrades as profitable firms, but have a smaller decrease in frequency of upgrades because of increase in volatility. While the outperformance in terms of non-price-related measures is not a necessary condition for my explanation of the profitability anomaly - the value of option-like equity increases with volatility even if expected cash flows remain the same - the presence of such outperformance further supports the idea that, all else equal, unprofitable firms are better hedges against recessions than other firms.

5.4 Cross-Sectional Regressions

Table 4 tests robustness of the results in Tables 2 and 3 by performing firm-level Fama-MacBeth (1973) regressions of future stock returns on firm characteristics that include the standard list of controls (market beta, size, market-to-book, momentum, short-term

[15] Available at https://www.dropbox.com/s/hjiz2otrk5bkbd3/Robustness%20Profitability%20blind.pdf?dl=0

reversal), profitability measures and firm-level sensitivity to VIX changes (γ_{VIX}). γ_{VIX} is the variable I use for sorting firms into the base assets for FVIX, and it is defined as the slope from the regression of the firm's returns on the market and the change in VIX. The regression, recorded in the Data section as equation (2), is performed each month using daily returns from this month only). I prefer γ_{VIX} to firm-level β_{FVIX} estimates, because cross-sectional regressions do not require forming the factor-mimicking portfolio and allow to escape the estimation error from factor-mimicking.

In order to eliminate the impact of skewness and outliers, I transform all independent variables into ranks confined between zero and one. In each month, all firms in my sample are ranked in the ascending order on the variable in question and then I assign to each firm its rank instead of the ranking variable, with zero assigned to the firm with the lowest value of the variable. I then divide the rank by the number of firms with valid observations in each month, to ensure the rank is between zero and one. Since the ranks are between zero and one, the coefficients in Table 4 can be easily interpreted as the difference in expected returns between the firms with the lowest and highest values of the variable.

Panel A considers the standard sample for this paper, stocks priced at at least $5 when profitability is measured (at the end of the preceding fiscal year). Columns one and three regress future returns on controls and either profitability or gross profitability. I find that the profitability and gross profitability anomalies are large and significant. The slope on (gross) profitability estimates the expected return differential between the most and least profitable firms at (61.5) 53.2 bp per month, t-statistic (4.37) 3.31, quite close to what Table 3 estimates the profitability anomaly to be in the portfolio sorts.

Columns two and four add γ_{VIX}, the measure of aggregate volatility risk, and show that the profitability anomaly is reduced to statistically insignificant values, even though the point estimates are still sizeable. It is also interesting to notice that market-to-book, another, but different option-likeness measure, loses significance controlling for aggregate volatility risk, similar to what Barinov and Chabakauri (2022) find.

Panel B expands the sample to encompass all firms, including ones priced below \$5, and finds, in columns one and three, that the profitability anomaly is largely unaffected: it declines by roughly 12 bp per month, but remains statistically significant. Columns two and four also confirm that the aggregate volatility risk explanation works arguably even better in the bigger sample, as the point estimates of the profitability anomaly are within 18 bp of zero and their t-statistics are below one controlling for γ_{VIX}.

Overall, Table 4 suggests that the profitability anomaly and its aggregate volatility risk explanation are robust to using cross-sectional approach and to expanding the sample to include stocks priced below \$5.

6 Profitability Anomaly in Cross-Section

6.1 Profitability Anomaly and Distress

The aggregate volatility risk explanation of the profitability anomaly hypothesizes that low profitability firms have low expected returns, because they are hedges against aggregate volatility increases due to convexity of their equity values coming from the fact that their equity is similar to a call option close to being in the money. The immediate implication is that the profitability anomaly should then be present only among distressed firms, and the FVIX factor should be able to explain why that happens.

Table 5 tests this hypothesis by performing conditional double sorts first on a popular measure of distress, Ohlson's (1980) O-score and then on (gross) profitability and reports estimates of the profitability anomaly, defined as the Carhart alpha of the high-minus-low profitability portfolio, separately in each distress quintile. Similar to Table 3, Panel A in Table 5 deals with the profitability anomaly of Fama and French (2006), and Panel B looks at closely related, but distinct, gross profitability anomaly of Novy-Marx (2013).

Panel A reports that, strongly consistent with the volatility risk explanation, the profitability anomaly is concentrated exclusively in the top O-score quintile. In other O-score quintiles, it is at most 5 bp per month, and almost always below 10 bp per month, while in the top O-score quintile it is at 44 bp per month, t-statistic 1.87. Panel B looks at the gross profitability anomaly of Novy-Marx (2013) and reports similar evidence. In the sample with enough information to calculate O-score, the gross profitability anomaly turns out to be stronger than the profitability anomaly, and hence it is visible at around 25 bp (insignificant) in the bottom four O-score quintiles and then spikes to 70 bp per month, t-statistic 3.84, in the top O-score quintile.

The middle rows in the sub-panels report the alphas after controlling for aggregate volatility risk and show that controlling for FVIX significantly reduces the profitability anomaly in the top O-score quintile, as well as the difference in the strength of the anomaly between distressed and healthy firms. The last rows of each panel present evidence that FVIX betas of the high-minus-low profitability strategy also increase in absolute magnitude along with the alpha across O-score quintiles. For example, in Panel A FVIX beta of this strategy goes from -0.099, t-statistic -0.71, to -0.717, t-statistic -4.26.

In untabulated results, I confirm that the results in Table 5 are robust to using the CAPM or the Fama-French model as a benchmark. The profitability anomaly is stronger in those models, but the two-factor ICAPM with FVIX produces even stronger reduction in the profitability anomaly and its dependence on O-score than what Table 5 reports.

To sum up, Table 5 shows that, consistent with my hypothesis, the profitability (and gross profitability) anomaly is driven by the equity value convexity introduced by distress and the consequent hedging ability against aggregate volatility risk. The profitability anomaly is indeed significantly stronger in the distressed firm subsample, and this regularity is largely explained by the fact that the high-minus-low profitability strategy (that shorts unprofitable firms) is exposed to aggregate volatility risk the most in the distressed firm subsample (in which unprofitable firms are the best hedges against aggregate volatility risk).

6.2 Profitability Anomaly and Idiosyncratic Volatility

The aggregate volatility risk explanation of the profitability anomaly suggests that unprofitable/distressed firms perform better than standard asset-pricing models (like the CAPM or the Fama-French model) predict when aggregate volatility increases, because the increased volatility, all else equal, benefits option-like firms more, and equity of distressed firms is option-like due to limited liability.

The first necessary condition for unprofitable firms being a hedge against aggregate volatility risk is the existence of a link between firm-level (essentially idiosyncratic) volatility and market/aggregate volatility. This link has been established in Barinov (2013), Duarte et al. (2012), and Herskovic et al. (2016).

The second necessary condition is the existence of significant idiosyncratic volatility (IVol) in the group of firms creating the profitability anomaly, because for the volatility of low volatility firms will increase only slightly (by absolute magnitude) as the market becomes more volatile, and this increase is unlikely to have a sizable impact on the equity value no matter if it is convex or not.[16]

[16]Barinov (2017) sorts firms on IVol and finds that total and even percentage sensitivity of firm IVol to changes in market-wide average IVol increases across IVol quintiles.

The second necessary condition suggests that the profitability anomaly should be stronger for high IVol firms, and this regularity should be explained by aggregate volatility risk. Table 6 tests this hypothesis by presenting the alphas and FVIX betas of the high-minus-low profitability portfolio across IVol quintiles.[17] Similarly to Table 5, Panel A of Table 6 considers the profitability anomaly, and Panel B looks at the gross profitability anomaly.

The evidence in Table 6 strongly confirms the hypotheses in the paragraph above. In both panels and irrespective of the benchmark model used, the profitability anomaly is absent in all IVol quintiles except for the top one, in which it is at 71 (88.5) bp per month in Panel A (B), always significantly higher than in other quintiles. FVIX betas behave similarly, staying negative, but insignificant in all idiosyncratic volatility quintiles except for the top one. Controlling for FVIX largely explains the difference in the profitability anomaly between low and high IVol firms, and either explains or significantly reduces the huge profitability anomaly in the top IVol quintile.[18]

7 Robustness Tests

7.1 Alternative Profitability Measures of Ball et al.

In a recent series of papers, Ball et al. (2015, 2016, 2019) refine the profitability measure and create even stronger profitability anomaly, which I attempt to explain in Table 7 using the same two-factor ICAPM with the market factor and FVIX.

Panel A sorts firms into quintiles using operating profitability from Ball et al. (2015).

[17]Table 6 presents conditional sorts: firms are first sorted on IVol and then on profitability.

[18]In Panel A, FVIX betas of the high-minus-low profitability strategy in the top IVol quintile are economically large, but statistically marginally significant. This is not unexpected, since volatile firms by definition have "noisy" returns that vary a lot for firm-specific reasons unrelated to any risk factor. Thus, all risk loadings of high IVol firms will have noisy estimates.

The difference between operating profitability and gross profitability of Novy-Marx (2013) that I used in the rest of the paper is that in the case of operating profitability in the denominator SG&A expenses are deducted from total revenue along with costs of goods sold (COGS), and then research and development (R&D) expenses are added back, while the numerator uses book value of total assets rather than book value of equity.

With value-weighting and stocks priced below $5 at the portfolio formation date removed from the sample, operating profitability creates the anomaly similar in magnitude to the one in Table 3. Compared with Panel B, where I look at gross profitability, the high-minus-low quintile spread has the CAPM/Carhart alpha of 47/54 bp per month (vs. 67/47 bp per month in Panel B of Table 3).[19]

The ability of FVIX to explain the profitability anomaly declines somewhat as I switch from gross profitability to operating profitability. Comparing Panel B of Table 3 vs. Panel A of Table 7, I find that adding FVIX to the CAPM reduces the high-minus-low alpha spread to 16 bp per month in Table 3 vs. 23 bp per month in Table 7 (both insignificant), while adding FVIX to the Carhart model reduces the alpha spread to 14 bp vs. 33 bp per month (the latter being significant).[20]

Panel B of Table 7 sorts on cash-based profitability of Ball et al. (2016), which augments operating profitability above by adding back accruals estimated following Sloan (1996).[21]

[19]Another reason why the operating profitability anomaly in Panel A of Table 7 is weaker than the one reported in Ball et al. (2015), beyond dropping penny stocks, is that the sample period is more recent (1986-2014), and Ball et al. report that the operating profitability anomaly weakens in the second part of their sample (1963-2013).

[20]The difference between gross profitability and operating profitability is the presence of SG&A expenses in the numerator of the latter. In untabulated results, I add R&D expense back to operating profitability and observe that the explanatory power of FVIX and the monotonic relation between FVIX betas and profitability are largely restored, and the operating profitability anomaly is weakened: in the Carhart alphas, the high-minus-low spread is 29 bp per month, t-statistic 1.89, and adding FVIX reduces the alpha spread to 6 bp per month, t-statistic 0.44. Since R&D are strongly related to growth options (the other source of firm value convexity inversely related to distress, I conclude that the lower explanatory effect of operating profitability comes from the confounding effect of R&D.

[21]See Data Appendix at https://www.dropbox.com/s/506dblsmw5p7lty/Data%20Appendix%20Profitability.pdf?dl=0

The results are similar to Panel A, though I find that FVIX can explain the high-minus-low alpha spread better than in Panel A: the spread is at 39 bp per month in both the CAPM and Carhart alphas and declines to 15 and 19 bp per month (both insignificant) once FVIX is added.[22] The U-shape in FVIX betas is still present, and removing R&D expenses from cash-based profitability (results not tabulated) again makes FVIX betas more monotonically and negatively related to profitability.

Ball et al. (2019) divide book-to-market into retained earnings-to-market and contributed capital to market, and show that the latter is not priced, while the former is driving the value effect. The interpretation Ball et al. offer is that retained earnings capture long-run profitability and thus the value effect is just another manifestation of the profitability anomaly.

In Panel C of Table 7, I sort firms into quintiles on retained earnings divided by the market cap and find, just like Ball et al. (2019) do, that the high-minus-low alpha spread is strong in the CAPM (76 bp per month, t-statistic 2.82) and weak in the Carhart alphas (30 bp per month, t-statistic 1.62). This is consistent with the argument in Ball et al. that the value-minus-growth return spread and the spread created by sorting on retained earnings to market are the same thing, and this is why the HML factor subsumes the retained earnings to market effect on returns.

FVIX contributes significantly to explaining the relation between retained earnings and future returns. The high-minus-low quintile alpha spread is reduced to insignificance when FVIX is added to the CAPM, the alphas of all quintiles but one also become insignificant,

for the exact definition of cash-based profitability

[22]The relatively weak profitability anomaly compared to Ball et al. (2016) is again caused by the exclusion of stocks priced below $5 at the portfolio formation date and a more recent sample period. In untabulated results, I find that FVIX can still explain the stronger profitability anomaly with stocks priced below $5 included back into the sample.

and FVIX betas are negatively, significantly, and monotonically related to retained earnings. Similar to the rest of my paper, firms with low retained earnings (a long history of low profitability) are hedges against volatility risk.

The ability of FVIX to largely explain the relation between retained earnings and future returns raises an interesting question of whether FVIX can explain the value effect, since Ball et al. (2019) argue that retained earnings are the true variable behind the value effect. Barinov and Chabakauri (2022) use FVIX to explain the value effect and find that a third factor that mimics innovations to average idiosyncratic volatility (FIVol) is needed: while FVIX does contribute to explaining the value effect, FIVol does the heavy lifting. In untabulated analysis, I look at the sorts on the other part of book-to-market - the ratio of contributed capital to market value - and find that contributed capital is strongly and positively related to FVIX betas (while contributed capital is unrelated to alphas, as Ball et al., 2019, find). This positive relation is not surprising (Barinov, 2012, finds that IPOs and SEOs have positive FVIX betas and net stock issuance in the past five years is positively related to FVIX betas), but since retained earnings are negatively related to FVIX betas, the positive relation between (the unpriced variable of) contributed capital and FVIX betas obscures the negative relation between book-to-market and FVIX betas needed to explain the value effect with FVIX.

7.2 Profitability Anomaly when VIX is Increasing

Table 8 aims to complement Figure 1 by providing direct evidence that, when VIX unexpectedly increases, unprofitable firms have positive alphas and the high-minus-low profitability strategy has negative alphas. In Panel A1, I look at CAPM alphas of high-minus-low profitability strategies based on various profitability measures discussed in Sections

5.3 and 7.1. The alphas are reported in three subsamples: months when change in VIX exceeds its 75th, or 80th, or 85th percentile. During those increasing-VIX months, CAPM alphas of the high-minus-low profitability strategies are negative (with the exception of the strategy from Ball et al., 2019, based on retained earnings) and economically sizeable, peaking at -42 bp to -76 bp per month. However, none of the alphas is statistically significant, most probably because of the small sample size and the focus on inherently volatile months.

Panel A2 looks at CAPM alphas of firms in the bottom profitability quintile and finds that those alphas are uniformly positive, economically large (peaking between 77 bp and 93 bp per month depending on the profitability measure used), but again statistically insignificant. The evidence in Panel A of Table 8 is consistent with what Figure 1 depicts focusing only on the Great Recession; Table 8 further shows that similar performance happens during other recessions and high-volatility episodes.

Since Panel B focuses on extreme volatility episodes, market betas of the high-minus-low profitability strategy and of unprofitable firms can also shift significantly. To control for that, in Panel B I make market beta conditional on the four commonly used state variables[23] and report Conditional CAPM alphas.

The alphas of high-minus-low profitability strategies in Panel B1 are uniformly more negative than those in Panel A1: they turn negative in the case of retained earnings sort and reach -33 bp per month, and for other profitability measures the Conditional CAPM alphas in Panel B1 peak between -0.87% and -1.54% per month. Five out of 15 alphas in Panel B1 are significant at the 10% level, and three more have t-statistics above 1.6

[23] Following Petkova and Zhang (2005), I use market dividend yield, default premium (yield spread between Baa and Aaa corporate bonds), 1-month Treasury bill rate, and term premium (yield spread between 10-year and 1-year Treasuries). For more discussion of Conditional CAPM and its relation to the profitability anomaly, see Section 4 of online Robustness Appendix.

in absolute magnitude. I conclude that there is reliable evidence that the high-minus-low profitability strategy underperforms when VIX witnesses large enough increases.

Similarly, Panel B2 looks at Conditional CAPM alphas of the bottom profitability quintile and reports uniformly more positive alphas than Panel A1. The alphas now peak between 1.37% and 1.57% per month, all 15 of them are positive (as in Panel A2), but in contrast to Panel A2 8 out of 15 alphas in Panel B2 are significant at the 10% level. Hence, there is also reliable evidence that underperformance of high-minus-low profitability strategies during VIX increases is driven by positive alphas of unprofitable firms during those months.

Panel C looks at the high-minus-low profitability strategy followed in subsample of high IVol/high O-score firms, as in the second rightmost columns of Tables 5 and 6, and reports its CAPM alphas (Panel C1) and Conditional CAPM alphas (Panel C2). Nine of 12 CAPM alphas and all 12 Conditional CAPM alphas are negative; however, almost all alphas are insignificant. The lack of power is caused by the fact that now the sample is small not only in terms of time-series (as in Panels A and B of Table 8), but also in terms of cross-section (the strategies in Panels C use only 20% of firms with the highest IVol/O-score). The reason why alphas in Panel C are generally lower than in the first two columns of Panels A1 and B1 is that in the full sample the alpha of the high-minus-low profitability strategy is higher for high IVol/O-Score firms and greater underperformance is needed to make it negative.[24]

[24]Ideally, of course, alphas of the high-minus-low profitability strategies in Panel C would be reliably negative when VIX is increasing, so probably the relatively small and insignificant alphas in Panel C also reflect the trouble FVIX had explaining the respective alphas in Panel B of Table 5 and Panel B of Table 6.

8 Additional Tests

This section briefly summarizes results of additional tests that are reported and discussed in the online Robustness Appendix.[25]

8.1 Alternative Volatility Risk Factors

Adrian and Rosenberg (2008) derive from Component GARCH (C-GARCH) two volatility risk factors based on the long-run and short-run volatility components and show that these factors (SR and LR, respectively) are priced. In Section 3.1 of the online Robustness Appendix, I attempt using these factors instead of FVIX and find that only SR contributes to explaining the profitability anomaly and explains roughly 50% of it. I also find that FVIX spans SR in the meaning of spanning tests in Barillas and Shanken (2017, suggesting that FVIX picks up short-run volatility risk.[26]

VIX uses more information than C-GARCH to form its volatility forecast, so it is not surprising that SR explains a smaller fraction of the profitability anomaly than FVIX. This fraction is cleaner, however, as C-GARCH forecast focuses on physical volatility measure and does not pick up risk aversion or volatility risk premium that are parts of VIX.

McQuade (2018) presents a model predicting that the distress risk puzzle of Dichev (1998), a regularity related to the profitability anomaly, should be explained by the long-run volatility component. My results based on SR and LR factors from Adrian and Rosenberg (2008) suggest that my explanation of the profitability anomaly is different.

[25] Available at https://www.dropbox.com/s/hjiz2otrk5bkbd3/Robustness%20Profitability%20blind.pdf?dl=0

[26] The VIX index that FVIX is based on is implied volatility of one-month options on S&P 100, so it is expected that FVIX will be picking up short-run volatility risk.

8.2 Lottery and Skewness Factors

Bali et al. (2020) suggest using an empirical factor based on expected skewness to explain the profitability anomaly. Bali et al. (2017) also cover a related lottery factor based on maximum daily returns in the past month. In Section 2 of the online Robustness Appendix, I perform spanning tests in the spirit of Barillas and Shanken (2017) and find that FVIX can explain the alphas of the lottery and skewness factors, but not the other way around, suggesting that those two factors proxy for FVIX and this is why the skewness factor can contribute to explaining the profitability anomaly.

8.3 The Role of Downgrades

Avramov et al. (2013) find that several anomalies, including the distress risk puzzle, are concentrated around credit rating downgrades. Removing from the sample all stocks that suffered a downgrade six months before or six months after portfolio formation renders these anomalies insignificant and suggests that the profit one can make trading on these anomalies comes from a handful of stock-months close to a downgrade (assuming that the firms that suffer the downgrades are available for shorting).

In Section 1 of the online Robustness Appendix, I perform the same exercise and find that omitting downgrades does not impact the magnitude of the profitability anomaly. This result is consistent with the finding in Avramov et al. (2013) that the value effect is unaffected by omitting downgrades and the conclusion of Fama and French (2015) that their value factor, HML, is redundant in the presence of RMW, the profitability factor.

8.4 Conditional CAPM

O'Doherty (2012) finds that the Conditional CAPM is capable of partially explaining the distress risk puzzle of Dichev (1998). Consistent with predictions of my model in the Theory Appendix, in Section 4 of the online Robustness Appendix, I find that market beta of the high-minus-low profitability portfolio increases in recessions, making the portfolio more risky than what the CAPM would suggest. The Conditional CAPM that takes the countercyclicality of the market beta into account explains about one-third of the profitability anomaly. I also find that FVIX largely subsumes the effect of conditioning variables on the alpha of the high-minus-low profitability portfolio and thus represents a broader explanation of the profitability anomaly.

8.5 Tradable FVIX

In the paper, I follow the long factor-mimicking tradition starting with Breeden et al. (1989) to run a single full-sample regression to create FVIX to increase precision of the estimates. The full-sample regression can potentially introduce look-ahead bias - though investors are also likely to be more informed than an econometrician and to have had an idea about market implied volatility and how to mimic it before VIX emerged. In Section 3.2 of the online Robustness Appendix, I verify that the results in the paper are robust to using fully tradable FVIX that is created by running an expanding window regression that uses the first years as the learning sample and then in period t uses all data from the start of the sample to period t-1 to form FVIX. I refrain from using this version of FVIX as the main specification because doing so would cause me to forego the first years in the sample that contain several important high-volatility episodes (e.g., October 19, 1987 market crash).

8.6 Duration and Profitability Anomaly

Several papers, starting with Dechow et al. (2004) and Lettau and Wachter (2007), show that equity duration is negatively priced. Low duration firms are usually value firms and unprofitable firms; a recent paper by Gonçalves (2021) thus shows that in cross-sectional regressions, equity duration subsumes both the value effect and the profitability anomaly.

In Section 6 of the online Robustness Appendix, I first regress the duration factor, DUR, based on duration portfolios in Gonçalves (2021)[27] on FVIX and then FVIX on the duration factor. I find that while there is a statistically significant negative relation between DUR and FVIX, economically this relation is weak: DUR explains at most 5 bp of FVIX alpha, and FVIX explains 10-25 bp of DUR alpha. I then use FVIX and DUR, separately and together, to explain the alpha of RMW. I find that FVIX/DUR betas of RMW do not materially change whether I use FVIX and DUR separately or together. I also find that DUR can explain at most 25% of RMW alpha, while FVIX explains roughly two-thirds.[28] I conclude that the duration explanation of the profitability anomaly in Gonçalves (2021) and my aggregate volatility risk explanations are two complementary explanations with little overlap.

9 Conclusion

The paper shows that the profitability anomaly is explained by aggregate volatility risk. Unprofitable firms have convex equity that responds favorably, holding all else equal, to increases in aggregate volatility. Equity convexity arises from limited liability, which makes

[27]I thank Andrei Gonçalves for making the returns of duration portfolios available at https://andreigoncalves.com/research/.

[28]The fact that the DUR factor cannot explain the profitability effect in time-series regressions, while Gonçalves (2021) shows that duration subsumes profitability in cross-sectional regressions, suggest that duration is priced as a firm characteristic, but not as a risk proxy.

equity resemble a call option on the assets with the strike price equal to the price of debt, and the fact that unprofitable firms tend to be distressed and thus their option-like equity is close to "being in the money".

Aggregate volatility risk also subsumes the new profitability factor that has recently been suggested as a factor to complement or replace some of the standard Fama-French (1993) factors.

Consistent with the idea that unprofitable firms are hedges against aggregate volatility due to being distressed and having option-like equity, the paper finds that the profitability anomaly comes almost exclusively from the top distress quintile, in which the spread in aggregate volatility risk exposure between the most and least profitable firms is expectedly the widest.

The aggregate volatility risk explanation of the profitability anomaly relies on the fact that option-like equity of unprofitable/distressed firms benefits from increases in idiosyncratic volatility, which tend to coincide with increases in market volatility (see, e.g., Barinov, 2013, Duarte et al., 2012, and Herskovic et al., 2016, for more evidence). Since the increases in idiosyncratic volatility are likely to matter more for volatile firms, the profitability anomaly should be stronger for volatile firms. Consistent with that, the paper finds that the profitability anomaly exists only in the top idiosyncratic volatility quintile, which is also the only quintile, in which the high-minus-low profitability strategy is significantly exposed to aggregate volatility risk.

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Table 1. Descriptive Statistics

Panel A looks at the median values of distress measures across profitability quintiles. The distress measures include market leverage (Lev), O-score, Z-score (times -1), distance to default (DD) from Bharath and Shumway (2008) (times -1), credit rating (Cred), and expected default probability (EDP) from Campbell et al. (2008). Profitability is net income before extraordinary items (Compustat ib item) divided by book value of equity (ceq plus txdb). The quintiles are formed using NYSE (exchcd=1) breakpoints and are rebalanced annually. Panel B reports, for the same quintiles, median values of several firm-specific volatility measures - idiosyncratic volatility (IVol), analyst disagreement (Disp), analyst forecast error (Error), volatility of cash flows (CVCFO) and earnings (CVEarn). Panel C looks at growth options measures - market-to-book (MB), investment growth (IG), investment-to-assets (ITA), and sales growth (SG). Panel D considers overall measures of convexity: non-linearity of returns-earnings relation (SUE flex) and firm value responsiveness to volatility movements (TVol sens). Detailed definitions of all variables are in the Data Appendix. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2014. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

Panel A. Profitability and Distress

	Low	Prof2	Prof3	Prof4	High	L-H	t(L-H)
Lev	0.253	0.269	0.238	0.179	0.102	0.151	6.69
O-Score	-0.623	-1.758	-1.918	-2.157	-2.362	1.739	20.9
-Z-Score	-2.753	-3.039	-3.378	-3.870	-4.687	1.934	21.4
Cred	12.72	10.41	9.169	8.006	8.139	4.579	28.7
-DD	-4.587	-5.879	-6.863	-7.636	-8.153	3.567	20.3
EDP	0.033	0.020	0.017	0.016	0.017	0.016	10.8

Panel B. Profitability and Firm-Level Volatility

	Low	Prof2	Prof3	Prof4	High	L-H	t(L-H)
IVol	0.023	0.018	0.017	0.017	0.018	0.005	7.89
Disp	0.145	0.060	0.038	0.031	0.030	0.115	9.75
CVEarn	1.851	0.894	0.538	0.458	0.480	1.372	13.5
CVCFO	1.498	1.095	0.899	0.788	0.740	0.757	8.45
Error	0.332	0.161	0.112	0.087	0.082	0.250	8.35

Panel C. Profitability and Growth Options

	Low	Prof2	Prof3	Prof4	High	L-H	t(L-H)
MB	1.436	1.202	1.490	1.897	2.997	-1.562	-30.6
IG	0.067	0.117	0.126	0.174	0.225	-0.158	-15.0
ITA	0.031	0.045	0.056	0.060	0.067	-0.035	-22.9
SG	0.106	0.098	0.104	0.111	0.137	-0.030	-6.50
SG_{t+1}	0.105	0.137	0.161	0.176	0.215	-0.110	-16.3

Panel D. Profitability and Convexity

	Low	Prof2	Prof3	Prof4	High	L-H
SUE flex	0.061	0.039	0.036	0.034	0.039	0.022
t-stat	*19.2*	*12.9*	*9.19*	*7.81*	*10.3*	*4.71*
TVol Sens	1.230	1.048	0.964	0.970	0.893	0.337
t-stat	*13.9*	*13.2*	*12.8*	*11.9*	*9.87*	*8.46*

Table 2. RMW factor and Aggregate Volatility Risk

Panel A presents descriptive statistics of the five Fama-French (2015) factors and FVIX factor. FVIX is the factor-mimicking portfolio that tracks daily changes in VIX. Panel B presents the estimates of factor models fitted to returns to the RMW factor of Fama and French (2015). RMW buys (shorts) firms in the top 30% (bottom 30%) on profitability. The returns to the strategy are value-weighted and computed separately for small (below NYSE marker cap median) and large firms, and then averaged. The sorts on profitability are independent of size and use NYSE breakpoints. Panel B/C presents the estimates of factor models fitted to return to RMW/FVIX. Panel D presents average returns and alphas of FVIX in subperiods based on ΔVIX values, as indicated by the first column. The second column reports the number of months (NObs) that belong to the subperiods. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2014.

Panel A. Descriptive Statistics for Asset-Pricing Factors

	Mean	**StDev**	**Sharpe**	α_{CAPM}	**Appraisal**	**Skew**	**Kurt**
MKT	0.656	4.514	0.145			-0.933	5.731
SMB	0.104	3.068	0.034	0.010	0.003	0.504	8.380
HML	0.231	3.012	0.077	0.352	0.121	0.087	6.100
MOM	0.551	4.686	0.118	0.669	0.145	-1.655	15.222
CMA	0.330	1.999	0.165	0.441	0.238	0.467	4.862
RMW	0.368	2.475	0.149	0.489	0.209	-0.562	14.104
FVIX	-1.342	6.174	-0.217	-0.468	-0.338	1.009	6.006

Panel B. RMW on FVIX

	Raw	**CAPM**	**ICAPM**	**FF**	**+FVIX**	**Carhart**	**+FVIX**
α	0.362	0.482	0.119	0.413	0.180	0.374	0.134
t-stat	*2.41*	*3.35*	*0.70*	*3.05*	*1.44*	*2.84*	*1.13*
β_{MKT}		-0.184	-1.236	-0.102	-0.836	-0.089	-0.832
t-stat		*-3.84*	*-3.55*	*-2.18*	*-5.18*	*-2.19*	*-4.99*
β_{SMB}				-0.309	-0.220	-0.312	-0.222
t-stat				*-3.29*	*-2.81*	*-3.20*	*-2.71*
β_{HML}				0.208	0.170	0.225	0.189
t-stat				*2.26*	*2.18*	*2.58*	*2.52*
β_{Mom}						0.048	0.054
t-stat						*1.02*	*1.27*
β_{FVIX}			-0.789		-0.536		-0.543
t-stat			*-3.15*		*-4.58*		*-4.55*

Panel C. FVIX on RMW

	Raw	CAPM	FF	+RMW	+CMA	Carhart	+RMW	+CMA
$\boldsymbol{\alpha}$	-1.342	-0.468	-0.445	-0.357	-0.300	-0.453	-0.371	-0.314
t-stat	*-4.28*	*-4.47*	*-3.69*	*-3.49*	*-3.59*	*-3.68*	*-3.58*	*-3.73*
$\boldsymbol{\beta}_{MKT}$		-1.333	-1.370	-1.391	-1.410	-1.367	-1.387	-1.405
t-stat		*-36.0*	*-32.8*	*-38.4*	*-48.2*	*-32.1*	*-37.5*	*-47.3*
$\boldsymbol{\beta}_{SMB}$			0.165	0.100	0.102	0.165	0.097	0.098
t-stat			*4.72*	*3.72*	*3.77*	*4.89*	*3.78*	*3.89*
$\boldsymbol{\beta}_{HML}$			-0.071	-0.027	0.043	-0.068	-0.019	0.062
t-stat			*-1.32*	*-0.55*	*0.60*	*-1.30*	*-0.38*	*0.85*
$\boldsymbol{\beta}_{Mom}$						0.010	0.021	0.030
t-stat						*0.58*	*1.36*	*1.91*
$\boldsymbol{\beta}_{RMW}$				-0.211	-0.236		-0.216	-0.246
t-stat				*-4.62*	*-5.16*		*-4.75*	*-5.25*
$\boldsymbol{\beta}_{CMA}$					-0.157			-0.174
t-stat					*-2.24*			*-2.43*

Panel D. FVIX in Subsamples

	NObs	Raw	CAPM	Carhart	FF5
$\boldsymbol{\Delta VIX > 4}$	49	6.722	-0.203	-0.179	0.131
t-stat		*6.43*	*-0.80*	*-0.57*	*0.40*
$\boldsymbol{\Delta VIX > 5}$	34	8.353	-0.063	0.083	0.850
t-stat		*6.25*	*-0.20*	*0.18*	*2.11*
$\boldsymbol{\Delta VIX > 6}$	24	11.231	0.323	0.403	1.604
t-stat		*8.59*	*0.39*	*0.35*	*1.69*
$\boldsymbol{\Delta VIX > 7}$	15	12.472	0.560	1.279	1.656
t-stat		*6.11*	*0.61*	*0.93*	*1.34*
$\boldsymbol{\Delta VIX > 8}$	12	13.441	0.628	1.339	1.507
t-stat		*5.47*	*0.63*	*0.82*	*1.06*

Table 3. Profitability Anomaly and Aggregate Volatility Risk

The table reports value-weighted alphas from the CAPM and Carhart (1997) model, as well as alphas and FVIX betas from the ICAPM with the market factor and FVIX and from the Carhart model augmented with FVIX (5-factor), across profitability and gross profitability quintiles. Profitability is net income before extraordinary items (Compustat ib item) divided by book value of equity (ceq plus txdb). Gross profitability is total revenue (sale) minus cost of goods sold (cogs) divided by book value of equity (ceq plus txdb). The quintiles are formed using NYSE (exchcd=1) breakpoints and are rebalanced annually. FVIX is the factor-mimicking portfolio that tracks daily changes in VIX. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2014. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

Panel A. CAPM as the Benchmark Model

Panel A1. Profitability Anomaly and Volatility Risk

	Low	Prof2	Prof3	Prof4	High	H-L
α_{CAPM}	-0.366	-0.055	0.007	0.017	0.200	0.566
t-stat	*-1.85*	*-0.52*	*0.09*	*0.19*	*2.22*	*2.44*
α_{ICAPM}	0.078	0.006	0.124	-0.057	0.078	0.000
t-stat	*0.51*	*0.06*	*1.34*	*-0.56*	*0.82*	*0.00*
β_{FVIX}	0.960	0.121	0.227	-0.169	-0.265	-1.226
t-stat	*3.09*	*1.14*	*3.11*	*-1.98*	*-3.78*	*-3.40*

Panel A2. Gross Profitability Anomaly and Volatility Risk

	Low	GProf2	GProf3	GProf4	High	H-L
α_{CAPM}	-0.272	0.020	-0.101	0.130	0.198	0.469
t-stat	*-1.93*	*0.20*	*-0.77*	*1.60*	*2.10*	*2.48*
α_{ICAPM}	-0.063	0.181	-0.029	0.065	0.057	0.120
t-stat	*-0.46*	*1.73*	*-0.25*	*0.82*	*0.55*	*0.65*
β_{FVIX}	0.426	0.331	0.149	-0.146	-0.304	-0.729
t-stat	*2.66*	*2.87*	*1.43*	*-2.06*	*-3.01*	*-3.04*

Panel B. Carhart Model as the Benchmark Model

Panel B1. Profitability Anomaly and Volatility Risk

	Low	Prof2	Prof3	Prof4	High	H-L
$\alpha_{Carhart}$	-0.251	0.107	0.094	0.115	0.233	0.484
t-stat	*-1.51*	*0.87*	*1.07*	*1.67*	*3.05*	*2.32*
$\alpha_{5-factor}$	0.030	0.116	0.057	0.148	0.134	0.103
t-stat	*0.21*	*0.98*	*0.58*	*1.94*	*1.61*	*0.57*
β_{FVIX}	0.621	0.003	-0.082	0.077	-0.222	-0.843
t-stat	*3.53*	*0.03*	*-1.42*	*1.14*	*-2.24*	*-3.30*

Panel B2. Gross Profitability Anomaly and Volatility Risk

	Low	GProf2	GProf3	GProf4	High	H-L
$\alpha_{Carhart}$	-0.180	-0.027	0.089	0.220	0.278	0.458
t-stat	*-1.59*	*-0.24*	*0.92*	*2.38*	*2.99*	*2.60*
$\alpha_{5-factor}$	-0.009	0.007	0.109	0.230	0.172	0.181
t-stat	*-0.09*	*0.06*	*1.07*	*2.17*	*1.76*	*1.03*
β_{FVIX}	0.392	0.075	0.029	0.017	-0.238	-0.631
t-stat	*3.46*	*0.82*	*0.30*	*0.20*	*-1.88*	*-3.00*

Table 4. Cross-Sectional Regressions

The table presents the results of firm-level Fama-MacBeth regressions run each month. The dependent variable is raw monthly return. All independent variables are ranks between 0 and 1. In each month, all firms in the sample are ranked in the ascending order on the variable in question and then each firm is assigned its rank, with zero (one) assigned to the firm with the lowest (highest) value of the ranking variable. The rank is then divided by the number of firms with valid observations in each month minus one, to ensure the rank is between zero and one. The controls are market-to-book (MB), size, cumulative return between month t-2 and t-12 (MOM), and return in the past month (REV). Detailed definitions of all variables are in the Data Appendix. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2014.

Panel A. Price $>$ 5					Panel B. All Firms				
	1	**2**	**3**	**4**		**1**	**2**	**3**	**4**
Beta	0.070	-0.001	0.033	-0.007	**Beta**	0.051	0.005	0.031	0.003
t-stat	*0.60*	*-0.03*	*0.28*	*-0.22*	**t-stat**	*0.48*	*0.21*	*0.28*	*0.12*
Size	-0.536	-0.237	-0.387	-0.186	**Size**	-0.893	-0.820	-0.722	-0.741
t-stat	*-2.38*	*-0.96*	*-1.71*	*-0.74*	**t-stat**	*-3.32*	*-2.54*	*-2.41*	*-1.91*
MB	-0.855	-0.373	-0.816	-0.273	**MB**	-0.858	-0.443	-0.861	-0.504
t-stat	*-3.99*	*-1.15*	*-4.19*	*-0.99*	**t-stat**	*-3.96*	*-1.32*	*-4.21*	*-1.49*
Mom	1.269	1.035	1.214	0.978	**Mom**	0.968	0.618	0.925	0.545
t-stat	*5.64*	*2.66*	*5.34*	*2.49*	**t-stat**	*3.86*	*1.35*	*3.69*	*1.18*
Rev	-1.837	-1.140	-1.860	-1.109	**Rev**	-2.519	-1.783	-2.536	-1.779
t-stat	*-10.0*	*-4.69*	*-10.0*	*-4.60*	**t-stat**	*-11.1*	*-5.95*	*-11.1*	*-5.90*
Prof	0.532	0.314			**Prof**	0.416	0.181		
t-stat	*3.31*	*1.21*			**t-stat**	*2.19*	*0.55*		
GProf			0.615	0.367	**GProf**			0.495	0.131
t-stat			*4.37*	*1.63*	**t-stat**			*3.36*	*0.72*
γ_{VIX}		-0.239		-0.206	γ_{VIX}		-0.189		-0.196
t-stat		*-2.23*		*-2.04*	**t-stat**		*-1.96*		*-1.99*

Table 5. Profitability Anomaly and Distress

The table reports value-weighted alphas and FVIX betas of the high-minus-low profitability strategy across O-score quintiles. The alphas come the Carhart (1997) model, as well as the Carhart model augmented with FVIX (5-factor). The high-minus-low profitability strategy is followed separately in each O-score quintile and involves buying the top profitability quintile and shorting the bottom profitability quintile. Profitability is net income before extraordinary items (Compustat ib item) divided by book value of equity (ceq plus txdb). Gross profitability is total revenue (sale) minus cost of goods sold (cogs) divided by book value of equity (ceq plus txdb). The profitability and O-score quintiles are formed using NYSE (exchcd=1) breakpoints and are rebalanced annually. FVIX is the factor-mimicking portfolio that tracks daily changes in VIX. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2014. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

Panel A. Profitability Anomaly and Distress

	Low	O2	O3	O4	High	H-L
$\boldsymbol{\alpha}_{Carhart}$	-0.076	0.016	0.047	-0.001	0.443	0.520
t-stat	*-0.54*	*0.11*	*0.29*	*0.00*	*1.87*	*2.31*
$\boldsymbol{\alpha}_{5-factor}$	-0.121	-0.209	-0.180	-0.268	0.119	0.240
t-stat	*-0.88*	*-1.51*	*-1.15*	*-1.44*	*0.52*	*1.05*
$\boldsymbol{\beta}_{FVIX}$	-0.099	-0.498	-0.501	-0.591	-0.717	-0.618
t-stat	*-0.71*	*-3.75*	*-3.46*	*-3.46*	*-4.26*	*-4.43*

Panel B. Gross Profitability Anomaly and Distress

	Low	O2	O3	O4	High	H-L
$\boldsymbol{\alpha}_{Carhart}$	0.368	0.381	0.409	0.226	0.702	0.334
t-stat	*2.48*	*2.17*	*2.00*	*1.18*	*3.84*	*2.13*
$\boldsymbol{\alpha}_{5-factor}$	0.243	0.262	0.252	0.096	0.467	0.224
t-stat	*1.54*	*1.41*	*1.18*	*0.46*	*2.61*	*1.38*
$\boldsymbol{\beta}_{FVIX}$	-0.274	-0.263	-0.346	-0.288	-0.519	-0.245
t-stat	*-2.00*	*-1.95*	*-1.91*	*-1.89*	*-4.21*	*-2.47*

Table 6. Profitability Anomaly and Idiosyncratic Volatility

The table reports value-weighted alphas and FVIX betas of the high-minus-low profitability strategy across idiosyncratic volatility quintiles. The alphas come the Carhart (1997) model, as well as the Carhart model augmented with FVIX (5-factor). The high-minus-low profitability strategy is followed separately in each idiosyncratic volatility quintile and involves buying the top profitability quintile and shorting the bottom profitability quintile. Profitability is net income before extraordinary items (Compustat ib item) divided by book value of equity (ceq plus txdb). Gross profitability is total revenue (sale) minus cost of goods sold (cogs) divided by book value of equity (ceq plus txdb). The profitability (idiosyncratic volatility) quintiles are formed using NYSE (exchcd=1) breakpoints and are rebalanced annually (monthly). FVIX is the factor-mimicking portfolio that tracks daily changes in VIX. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2014. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

Panel A. Profitability Anomaly and IVol

	Low	**IVol2**	**IVol3**	**IVol4**	**High**	**H-L**
$\boldsymbol{\alpha}_{Carhart}$	0.046	0.274	0.276	0.189	0.707	0.661
t-stat	*0.23*	*1.39*	*1.21*	*0.64*	*2.33*	*1.81*
$\boldsymbol{\alpha}_{5-factor}$	-0.001	0.238	0.163	0.055	0.362	0.363
t-stat	*-0.01*	*1.16*	*0.65*	*0.18*	*1.15*	*0.97*
$\boldsymbol{\beta}_{FVIX}$	-0.103	-0.080	-0.249	-0.297	-0.762	-0.658
t-stat	*-0.53*	*-0.58*	*-1.00*	*-1.10*	*-1.66*	*-1.75*

Panel B. Gross Profitability Anomaly and IVol

	Low	**IVol2**	**IVol3**	**IVol4**	**High**	**H-L**
$\boldsymbol{\alpha}_{Carhart}$	0.192	0.353	0.447	0.417	0.885	0.693
t-stat	*0.96*	*1.54*	*1.78*	*1.53*	*2.64*	*1.92*
$\boldsymbol{\alpha}_{5-factor}$	0.195	0.323	0.337	0.330	0.546	0.351
t-stat	*0.94*	*1.40*	*1.25*	*1.13*	*1.74*	*1.02*
$\boldsymbol{\beta}_{FVIX}$	0.007	-0.067	-0.242	-0.194	-0.748	-0.756
t-stat	*0.03*	*-0.41*	*-1.26*	*-0.77*	*-2.31*	*-2.92*

Table 7. Alternative Profitability Measures

The table reports value-weighted alphas from the CAPM and the Carhart model, as well as alphas and FVIX betas from the two-factor ICAPM with the market factor and FVIX and the Carhart model augmented with FVIX (5-factor). The models are fitted to the quintile portfolios sorted on operating profitability (Panel A), cash-based operating profitability (Panel B), and retained earnings divided by market value of equity (Panel C). Operating profitability is total revenue (revt) minus cost of goods sold (cogs) minus SG&A (xsga) plus R&D expenses (xrd) if available, divided by total assets (at) from the previous year. Cash-based operating profitability deducts accruals from the denominator of operating profitability above. Following Ball et al. (2016), accruals are defined as change in accounts receivable (rect) plus change in inventory (invt) plus change in prepaid expenses (xpp) minus in deferred revenue (drc plus drlt) minus change in accounts payable (ap). The quintiles are formed using NYSE (exchcd=1) breakpoints and are rebalanced annually. FVIX is the factor-mimicking portfolio that tracks daily changes in VIX. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2014. The sample excludes the stocks with per share price less than $5 on the portfolio formation date.

Panel A. Operating Profitability of Ball et al. (2015)

Panel A1. CAPM as Benchmark Model							Panel A2. Carhart Model as Benchmark Model						
	Low	**OProf2**	**OProf3**	**OProf4**	**High**	**L-H**		**Low**	**OProf2**	**OProf3**	**OProf4**	**High**	**L-H**
$\boldsymbol{\alpha}_{CAPM}$	-0.403	0.161	0.142	0.136	0.067	0.470	$\boldsymbol{\alpha}_{Carhart}$	-0.312	0.169	0.105	0.151	0.232	0.544
t-stat	*-3.26*	*1.53*	*1.59*	*1.80*	*0.63*	*2.70*	**t-stat**	*-2.40*	*1.96*	*1.34*	*2.17*	*3.26*	*3.42*
$\boldsymbol{\alpha}_{ICAPM}$	-0.147	0.135	-0.056	0.081	0.086	0.234	$\boldsymbol{\alpha}_{5-factor}$	-0.112	0.162	-0.034	0.111	0.214	0.326
t-stat	*-1.30*	*0.99*	*-0.53*	*1.05*	*0.84*	*1.33*	**t-stat**	*-1.05*	*1.68*	*-0.39*	*1.51*	*2.74*	*2.43*
$\boldsymbol{\beta}_{FVIX}$	0.555	-0.049	-0.420	-0.137	0.041	-0.515	$\boldsymbol{\beta}_{FVIX}$	0.451	-0.006	-0.305	-0.108	-0.040	-0.491
t-stat	*4.50*	*-0.35*	*-2.45*	*-2.26*	*0.43*	*-4.36*	**t-stat**	*2.99*	*-0.09*	*-3.12*	*-1.82*	*-0.51*	*-2.49*

Panel B. Cash-Based Profitability of Ball et al. (2016)

Panel B1. CAPM as Benchmark Model

	Low	CProf2	CProf3	CProf4	High	L-H
$\boldsymbol{\alpha}_{CAPM}$	-0.316	0.078	0.213	0.195	0.078	0.393
t-stat	*-2.59*	*0.61*	*2.31*	*2.36*	*0.84*	*2.46*
$\boldsymbol{\alpha}_{ICAPM}$	-0.059	-0.005	0.069	0.053	0.087	0.146
t-stat	*-0.53*	*-0.04*	*0.79*	*0.53*	*0.93*	*0.92*
$\boldsymbol{\beta}_{FVIX}$	0.533	-0.171	-0.303	-0.316	0.013	-0.520
t-stat	*5.34*	*-0.80*	*-3.04*	*-2.83*	*0.19*	*-5.14*

Panel B2. Carhart Model as Benchmark Model

	Low	CProf2	CProf3	CProf4	High	L-H
$\boldsymbol{\alpha}_{Carhart}$	-0.146	0.072	0.133	0.197	0.239	0.385
t-stat	*-1.17*	*0.77*	*1.81*	*2.81*	*3.27*	*2.76*
$\boldsymbol{\alpha}_{5-factor}$	0.035	0.004	0.015	0.104	0.226	0.190
t-stat	*0.32*	*0.05*	*0.21*	*1.28*	*2.87*	*1.46*
$\boldsymbol{\beta}_{FVIX}$	0.387	-0.143	-0.259	-0.217	-0.034	-0.421
t-stat	*4.26*	*-1.23*	*-5.18*	*-2.56*	*-0.50*	*-3.20*

Panel C. Retained Earnings over Market of Ball et al. (2019)

Panel C1. CAPM as Benchmark Model

	Low	RE2	RE3	RE4	High	L-H
$\boldsymbol{\alpha}_{CAPM}$	-0.282	0.094	0.187	0.294	0.481	0.763
t-stat	*-1.99*	*1.18*	*2.50*	*2.36*	*2.96*	*2.82*
$\boldsymbol{\alpha}_{ICAPM}$	-0.052	0.027	0.032	0.158	0.330	0.383
t-stat	*-0.39*	*0.35*	*0.42*	*1.30*	*2.00*	*1.48*
$\boldsymbol{\beta}_{FVIX}$	0.486	-0.147	-0.330	-0.288	-0.343	-0.829
t-stat	*3.75*	*-1.66*	*-3.28*	*-2.38*	*-2.47*	*-4.02*

Panel C2. Carhart Model as Benchmark Model

	Low	RE2	RE3	RE4	High	L-H
$\boldsymbol{\alpha}_{Carhart}$	0.022	0.143	0.135	0.195	0.319	0.297
t-stat	*0.20*	*1.97*	*2.19*	*1.98*	*2.47*	*1.62*
$\boldsymbol{\alpha}_{5-factor}$	0.124	0.107	0.033	0.092	0.186	0.062
t-stat	*1.03*	*1.54*	*0.54*	*0.89*	*1.58*	*0.36*
$\boldsymbol{\beta}_{FVIX}$	0.224	-0.082	-0.225	-0.227	-0.314	-0.538
t-stat	*2.21*	*-0.82*	*-3.45*	*-3.26*	*-2.66*	*-3.12*

Table 8. Profitability Anomaly in Subperiods of Increasing VIX

Panel A (B) presents (Conditional) alphas of high-minus-low profitability portfolios (left subpanels) and of bottom profitability quintiles (right subpanels). The top row of Panel A and B reports the variables, on which profitability sorts were perform to obtain the high-minus-low profitability portfolios and the bottom profitability quintiles. The left column of each subpanel reports the subsample, in which the alphas were estimated (months in which ΔVIX exceeds its 85th/80th/75th percentile). In its (right) left subpanel, Panel C reports (Conditional) CAPM alphas of high-minus-low profitability portfolios sorted on either profitability or gross profitability in either the top IVol quintile (HiIVol) or top O-score quintile (HiO). The Conditional CAPM makes the market beta a function of market dividend yield, default premium, Treasury bill rate, and term premium (defined in online Data Appendix). The definitions of the profitability measures are in headers of Table 3 and Table 7. The t-statistics (in italics) use the Newey-West (1987) correction for heteroskedasticity and autocorrelation. The sample period is from January 1986 to December 2014.

Panel A. CAPM Alphas in DVIX Percentile Subsamples

A1. Arbitrage portfolios

$\Delta VIX >$	Prof	GProf	OProf	CProf	RE
85th pctl	-0.362	-0.149	-0.763	-0.416	0.247
t-stat	*-0.54*	*-0.27*	*-1.37*	*-0.78*	*0.40*
80th pctl	-0.551	-0.436	-0.642	-0.218	0.024
t-stat	*-0.95*	*-0.84*	*-1.60*	*-0.59*	*0.04*
75th pctl	-0.227	-0.097	-0.234	0.115	0.329
t-stat	*-0.37*	*-0.18*	*-0.78*	*0.41*	*0.45*

A2. Unprofitable firms

$\Delta VIX >$	Prof	GProf	OProf	CProf	RE
85th pctl	0.588	0.615	0.654	0.515	0.484
t-stat	*0.66*	*0.75*	*0.79*	*0.62*	*0.57*
80th pctl	0.866	0.930	0.912	0.771	0.835
t-stat	*1.16*	*1.35*	*1.45*	*1.22*	*1.16*
75th pctl	0.256	0.238	0.300	0.152	0.256
t-stat	*0.39*	*0.41*	*0.63*	*0.32*	*0.40*

Panel B. Conditional CAPM Alphas in DVIX Percentile Subsamples

B1. Arbitrage portfolios

$\Delta VIX >$	Prof	GProf	OProf	CProf	REarn
85th pctl	-1.133	-0.727	-1.537	-1.090	-0.228
t-stat	*-1.63*	*-1.31*	*-2.75*	*-2.01*	*-0.38*
80th pctl	-1.085	-0.865	-1.075	-0.575	-0.334
t-stat	*-1.95*	*-1.79*	*-2.78*	*-1.61*	*-0.60*
75th pctl	-0.779	-0.562	-0.544	-0.137	-0.115
t-stat	*-1.46*	*-1.22*	*-1.63*	*-0.45*	*-0.18*

B2. Unprofitable firms

$\Delta VIX >$	Prof	GProf	OProf	CProf	REarn
85th pctl	1.575	1.460	1.570	1.393	1.315
t-stat	*1.66*	*1.70*	*1.77*	*1.54*	*1.45*
80th pctl	1.505	1.472	1.461	1.294	1.373
t-stat	*2.03*	*2.16*	*2.37*	*2.06*	*1.91*
75th pctl	0.831	0.707	0.735	0.561	0.745
t-stat	*1.38*	*1.34*	*1.62*	*1.22*	*1.27*

Panel C. Abritage Portfolios for High IVol/High O-score Firms

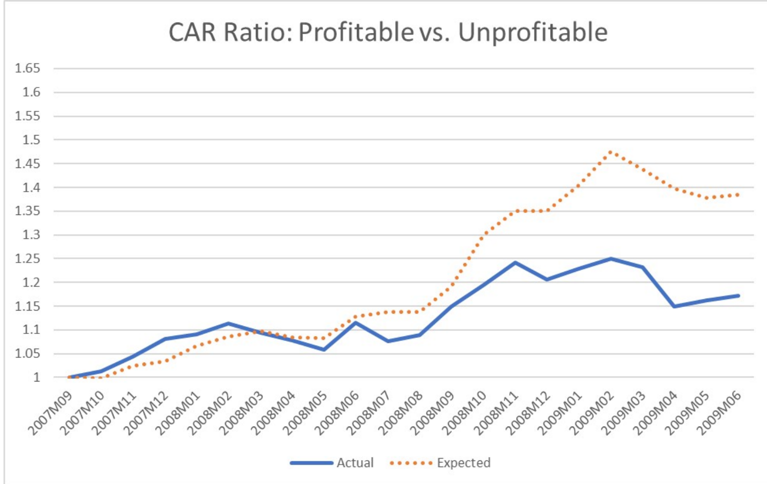
C1. CAPM Alphas

	Prof		GProf	
$\Delta VIX >$	HiIVol	HiO	HiIVol	HiO
85th pctl	0.054	0.150	-1.274	-0.152
t-stat	*0.08*	*0.14*	*-1.57*	*-0.16*
80th pctl	-0.026	-0.454	-1.007	-0.184
t-stat	*-0.04*	*-0.47*	*-1.87*	*-0.29*
75th pctl	-0.270	-0.116	-0.833	0.190
t-stat	*-0.53*	*-0.14*	*-0.73*	*0.32*

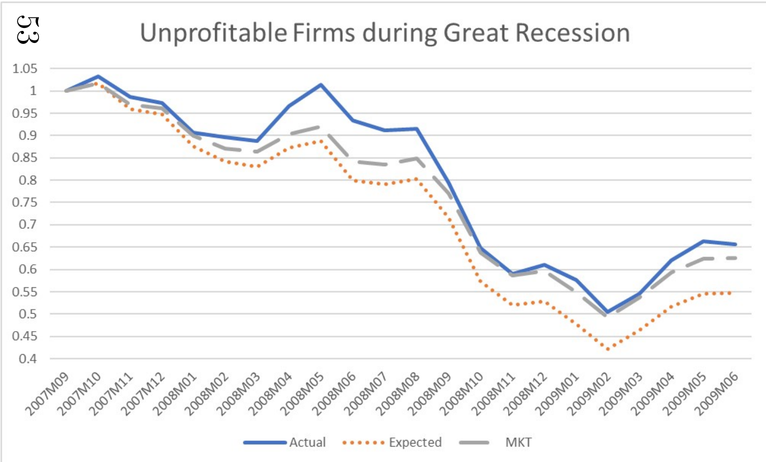
C2. Conditional CAPM Alphas

	Prof		GProf	
$\Delta VIX >$	HiIVol	HiO	HiIVol	HiO
85th pctl	-1.239	-1.119	-2.517	-0.041
t-stat	*-0.92*	*-0.85*	*-1.84*	*-0.04*
80th pctl	-0.037	-0.105	-0.761	-0.272
t-stat	*-0.03*	*-0.08*	*-0.70*	*-0.21*
75th pctl	-0.704	-1.114	-0.352	-0.447
t-stat	*-0.79*	*-1.02*	*-0.39*	*-0.37*

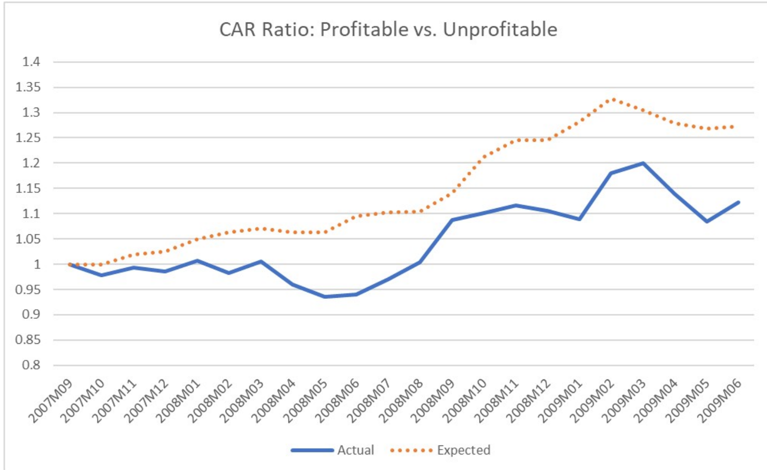
(A) Cumulative Return to Bottom Profitability Quintile



(B) Ratio of Cumulative Returns to Top and Bottom Profitability Quintile



(C) Cumulative Return to Bottom Gross Profitability Quintile



(D) Ratio of Cumulative Returns to Top and Bottom Gross Profitability Quintile

Figure 1

Unprofitable Firms and Profitability Anomaly during the Great Recession

Panel A (C) presents cumulative return to the bottom (gross) profitability quintile, as well as cumulative return of the CRSP market index, and expected cumulative return to the bottom (gross) profitability quintile (from the market model). Panel B (D) plots the ratio of cumulative returns to top and bottom (gross) profitability quintile, as well as its expected value from the market model fitted to the high-minus-low profitability portfolio.