Fair Value Assets and Variance Risk Premiums for Financial Stocks

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Abstract: Financial firms hold large amounts of fair value assets. However, some balance sheet values are based on quoted prices while others use model-based prices and manager inputs ("opaque assets"; i.e., Level 2 and Level 3 assets). I test if financial firms' holdings of opaque assets are associated with variance risk premiums in equity options. I find that firms with large holdings of Level 3 assets have larger spreads between implied volatilities and realized volatilities along with more negative straddle returns. These results hold conditional on several other factors including industry membership, option-implied risks, and a proxy of option mispricing. I also present evidence that for larger firms, Level 2 assets are negatively associated with variance risk premiums. Finally, I show that these relationships are strongest in the final years of the sample.

JEL Codes: G13, M40

Keywords: Opaque assets; information risk; variance risk premiums; straddles; financials

1. INTRODUCTION

In this paper, I investigate how information risk affects variance risk premiums in the equity option market. More specifically, I examine if financial firms who hold higher levels of opaque fair value assets have lower variance risk premiums and straddle returns compared to firms that hold assets whose values are more easily determined and verifiable. Following prior literature, I define opaque fair value assets as those designated as Level 2 and Level 3 assets. As McDonough, Panaretou, and Shakespeare (2020, p. 309) explain, the complexity of determining fair value and the information asymmetry between firms and investors is low for Level 1 assets. However, this is not necessarily true for Level 2 and Level 3 fair value assets. Instead, the use of discretion and the complexity of financial models generally increase from Level 1 to Level 2 and from Level 2 to Level 3 of the fair value measurement hierarchy.[1]

My focus on the financial sector is motivated by two empirical facts. As shown in Table 1, when I split my upcoming sample into financial and non-financial firms, it is clear that financial firms hold significantly more fair value assets compared to non-financial firms.[2] In particular, the statistics show that the mean fair value asset to total book asset ratio for financial firms (*FVAT*) is 26.1%, but for non-financial firms the ratio is only 10.5%. I also find that a large amount of fair value assets are in the Level 2 and Level 3 categories for financial firms (*LEVEL2AT* and *LEVEL3AT* respectively). Non-financials, on the other hand, have relatively few assets that fall in the Level 2 and Level 3 categories. Second, financial firms tend to have lower market-to-book ratios relative to non-financial firms. Thus, the pricing of book assets is of primary importance to

[1] Accounting Standards Codification (ASC) 820 provides guidance on the hierarchy of inputs for Level 1, 2, and Level 3 assets (Financial Accounting Standards Board [FASB] 2011). Level 1 assets use market quote prices and Level 2 assets use market prices to mark-to-model. However, Level 3 fair value assets use unobservable model inputs to derive a fair value and resulting unrealized gains and losses. Please note that ASC 820 was updated in 2018.

[2] Financial firms have two-digit SIC codes 60 – 67. Non-financial firms have any other SIC code.

the valuation of financial firms' stock and credit securities. Indeed, as Nissim (2013) states, unlike non-financial firms, a primary driver of equity value for financial firms is the book value of equity.[3] Thus, information risk of assets is likely a more important factor in the financial sector relative to other economic sectors.

The evidence of how opaque assets affect capital markets is mixed. Opaque fair value assets can lead to higher (perceived) risk for investors leading to lower-quality disclosures. This in term can affect market outcomes. The model of Lambert, Leuz, and Verrecchia (2007), for example, suggests that information quality can affect firms' equity beta and, consequently, affect firms' cost of capital. When examining fair value assets in the financial sector, Riedl and Serafiem (2011) suggest that a higher level of opaque assets may lead to higher equity betas. Empirically, they find evidence that Level 3 assets have stronger associations with firms' adjusted equity betas relative to Level 1 and Level 2 assets. Ayers (2016) investigates if a higher level of opaque assets influences credit ratings. He finds that conditional on several other factors, financial firms' holdings for Level 3 assets are negatively associated with their credit rating. In addition, when examining the financial crisis period of 2007-2009, Arora, Richardson, and Tuna (2014) find evidence that short-term credit yields and credit term structures are influenced by financial firms' holdings of Level 2 and Level 3 assets. They attribute this finding to more opaque financial assets having less reliability compared to other assets. Conversely, when focusing closed-end funds, Lawrence, Siriviriyakul, and Sloan (2016) find that Level 3 assets have similar value relevance to Level 1 and Level 2 assets. Kolev (2019) also concludes that investors appear to view the valuations of Level 3 assets as reliable and investors seem to incorporate their values into equity prices.

[3] Nissim (2013) specifically analyzes insurance firms but the idea holds for other financial firms.

In this study, I focus on the association between financial firms' holdings of opaque fair value assets with variance risk premiums and straddle returns. If the Black and Scholes (1973) assumptions hold, then empirically researchers should not observe a persistent difference between implied volatilities (IVs) and future realized volatilities. However, prior studies find a significant gap between IVs and realized volatilities (e.g., Carr and Wu, 2009), thus indicating that at least one of the Black-Scholes assumptions does not hold. The two main assumptions assumed to fail are that asset volatilities are known and constant and the stock prices do not jump. When these features are incorporated into option pricing models, option prices will become more expensive and this can generate a gap between option-implied risk measures and their real-world counterparts (e.g., Heston, 1993; Bates 1996). Thus, the study of variance risk premiums is related to other studies that investigate the capital market effects (i.e., equity and bond prices) but has many differences and advantages. For example, unlike equity prices, variance risk premiums cannot be generated by models with known and static variances (e.g., CAPM). Thus, a documented relationship between variance risk premiums and asset opacity would suggest that information risk goes beyond increasing expected variance. Variance risk premiums and straddle returns are also effective at removing "delta" risk from empirical tests and thus provide evidence on how opaque assets affect (perceived) higher-order risks. Moreover, unlike studies that use bonds and their associated yields, my use of options allows me to examine firms that may not have publicly traded credit products (e.g., Culp, Nozawa, and Veronesi, 2018).[4] Finally, the use of options allows me to easily control for ex ante risks in my empirical models.

I thus develop a one-sided hypothesis for how asset opacity is related to variance risk premiums. I hypothesize that financial firms that hold higher levels of opaque assets (i.e., Level 2

[4] Culp et al. (2018) also suggests that credit-like positions created from equity positions are more liquid than notes and bonds issued by the same underlying firm.

and Level 3 fair value assets) relative to their total asset base tend to have lower variance risk premiums and realized straddle returns. First, prior literature has shown that cost of capital measures are positively associated with opaque assets (Riedl and Serafiem, 2011). While other studies suggest that cost of capital proxies and variance risk premiums are weakly related (e.g., Carr and Wu, 2009), there is likely an overlap in equity and variance premiums. Similarly, opaque assets likely raise equity variances. While variance risk premiums and variance levels are not related in a Black-Scholes type model, empirically they are likely correlated (e.g., Cao and Han, 2013). Moreover, opaque assets may generate investor uncertainty about future asset variance. If higher levels of Level 2 and Level 3 assets create more variance uncertainty or if their valuations are ambiguous, then option pricing models such as Epstein and Ji (2013) suggest that option prices should increase relative to realized variances. This idea is related to the imperfect information model of Duffie and Lando (2001). If opaque assets have imperfect valuations, then this can create excess demand for short-dated insurance products again leading to lower variance risk premiums and option returns.[5]

To investigate my main hypothesis, I generate a large sample of monthly realized variance risk premiums and straddle returns for financial firms for the period after the 2008 financial crisis and link these variables to firms' reported fair value assets. My results are summarized as follows. First, I estimate a negative average variance risk premium and straddle return. This indicates that, on average, IVs are too high compared to future realized volatilities and investors generally suffer losses when purchasing at-the-money (ATM) straddles. Next, in univariate tests, I find evidence that firms that hold greater levels of opaque assets (i.e., more Level 2 and Level 3 assets) tend to

[5] The Duffie and Lando (2001) model is primarily concerned about credit spreads. However, the equity option market and credit markets are connected (e.g., Culp et al. 2018) and thus the results of Duffie and Lando (2001) are transferable to option prices.

have more negative variance risk premiums and straddle returns. In particular, after sorting within month-industries, I find firms in the highest quartile of opaque assets have variance risk premiums 4% lower than firms in the lowest quartile of opaque asset holdings. This difference is statistically significant at traditional levels.

Next, using multivariate regressions, I control for several other factors prior literature suggests is related to variance risk premiums. I find consistent evidence that firms that hold higher levels of Level 3 assets have lower variance risk premiums. When adjusting for firm-level factors such as firm size, profitability, leverage, and industry membership, I find a one-standard deviation increase in Level 3 assets scaled by total assets lowers variance risk premiums by roughly 3%.[6] I furthermore find the regression coefficients on Level 1 and Level 3 assets are significantly different. I also control for option-implied risks such as option-implied volatility, skew, and kurtosis. I continue to estimate a significant negative association between Level 3 assets and variance risk premiums. Moreover, when controlling for the option-implied risk measures, I estimate a conditional negative association between Level 2 assets and variance risk premiums. Combined, these results suggest that option-implied risks do not subsume the negative association between asset opacity and variance risk premiums. I also find that my results hold when I add a commonly used option mispricing proxy in the regression models. Finally, I confirm that these results generally hold when I use straddle returns as the dependent variable in my regression models.

I perform three additional tests. First, I split my sample based on firm size. Prior literature suggests that larger firms have better information environments and, thus, information risk due to

[6] As explained in more detail later, increasing fair value assets implicitly decreases non-fair value assets. Thus, the regression coefficients are imply the effect on variance risk premiums by shifting non-fair values assets into a fair value asset type.

opaque assets may be less for larger firms. Consequently, my prior results may be due exclusively to smaller firms. For smaller firms, I estimate a strong negative association between variance risk premiums and Level 3 assets. However, for larger firms, I estimate a significant negative coefficient between variance risk premiums and Level 2 assets. Thus, opaque assets appear to affect variance risk premiums for large and small financial firms, although the exact source of the relationship differs based on firm size. I also split the sample based on the observation years. Due to a heightened awareness of asset opacity levels by investors immediately following the financial crisis of 2008, I test if the relationship between asset opacity levels and variance risk premiums has weakened in recent years. However, my results are strongest in the last years of the sample. This pattern may be due to increased option coverage in recent years and, as more firms are included in the sample, I am better able to estimate the relationship between asset opacity levels and variance risk premiums. Finally, I find evidence that IVs have lower forecasting precision for future realized volatilities for firms with more opaque assets.

This study makes several contributions. First, as far as I am aware, this is the first study that examines the relationship between asset opacity and variance risk premiums in the financial sector. Again, I document that higher levels of opaque assets are associated with larger spreads between IVs and stock volatilities. My results also suggest that investors demand additional option-based protections when financial firms hold more opaque assets. My results should also be informative to theory. In particular, my results imply that asset opacity does not simply affect variance levels but, instead, may also influence investors' uncertainty about future variance outcomes. My results also suggest that asset opacity affects variance risk premiums even for firms with well-developed information environments. Finally, my results may be useful for industry professionals. For example, portfolio optimization and hedge ratios may incorporate IVs (e.g., Buss and Vikov, 2012; DeMiguel, Plyakha, Uppal, and Vilkov, 2013) but I show that IVs in financials are biased by the presence of opaque assets.

2. PRIOR LITERATURE AND EXPECTATIONS

2.1 Variance risk premiums

In this study, I investigate the cross section of variance risk premiums in the financial sector. Variance risk premiums arise theoretically in option pricing models due to several not mutually exclusive reasons. First, investors may not be able to fully hedge away stochastic shocks to variance (e.g. Heston 1993). As Carr and Wu (2009, p. 1316) explain, in a stochastic volatility model, a variance premium arises due to the conditional covariance between the normalized pricing kernel and realized variance. In short, if realized volatilities tend to rise when asset prices tend to drop, then on average IVs should exceed realized variances and the returns to delta-neutral option strategies should be negative (Bakshi and Kapadia, 2003). Another reason for observing negative risk premiums is asset price jumps. Because the price jumps cannot be hedged using a static hedge of other tradable instruments, jumps can be priced in the options market if the jump is not idiosyncratic. Indeed, when examining S&P500 future options, Broadie, Chernov, and Johannes (2007) find that option prices are affected by jumps in index prices and volatility itself. Another set of research suggests that unknown or "ambiguous" volatility can also generate a negative risk premium (e.g., Epstein and Ji, 2013). In these models, future volatility is known to have certain properties such as having a maximum or minimum value. However, investors cannot place probabilities on the variance outcomes or may not be able to observe the current variance value. In these cases, the resulting option prices will look, empirically, too high relative to future realized variance. Finally, other models rely on investor demand relative to dealers' ability to hold option inventory to explain option return patterns (Gârleanu, Pedersen, & Poteshman, 2009).

When analyzing individual equity options, studies have found that the variance risk premium in stock options is less negative when compared to index options (Driessen, Maenhout, & Vilkov, 2009). However, studies that attempt to explain the cross section of variance risk premiums in the individual equity option market are rarer. Cao and Han (2013), in contrast to theory, find that individual equity option returns are related to the level of firms' idiosyncratic variance. Lyle (2022) uses an accounting-based valuation model that suggests that fundamental ratios such as earnings-to-price and growth in earnings-to-price should have explanatory power for equity-level variance risk premiums. He finds that both factors, along with a stock's dividend yield, have a negative quadratic relationship with variance risk premiums.

The goal of this study is to further our understanding regarding which factors explain the cross section of variance risk premiums. More specifically, I examine how information risk on firms' balance sheets impacts the cross section of variance risk premiums. Following prior literature, I utilize the fair value hierarchy to define opaque assets within the financial sector.

2.2 Fair Value Hierarchy

The reporting for fair value assets was first mandated by United States GAAP under Statement of Financial Accounting Standards (SFAS) 157, *Fair Value Measurements* (FASB 2006). SFAS 157 became effective in 2008 with the option for early adoption allowed in 2007. SFAS 157 later became codified as ASC 820, *Fair Value Measurement*, in 2011.

Under both SFAS 157 and ASC 820, firms are required to provide details on their fair value assets and liabilities. In particular, firms must provide information about their fair value assets and liabilities after separating them into three types (i.e., the fair value hierarchy), denoted Level 1, Level 2, and Level 3 assets and liabilities. Level 1 inputs are defined as quoted prices that are available in active markets for identical assets or liabilities. Active markets are those in which transactions for the asset or liability occur frequently and trading volume is sufficient to provide pricing information on an ongoing basis. Moving down one level, Level 2 assets and liabilities use pricing inputs other than quoted prices in active markets. These inputs are either directly or indirectly observable. Thus, this category of fair value assets includes financial instruments that are valued using models or other valuation methodologies. For Level 2, substantially all of the valuation assumptions are observable throughout the full term of the instrument or can be derived or supported by market transactions. Finally, Level 3 assets and liabilities use pricing inputs that are generally less observable from objective sources. These inputs may be used with internal models that require managerial estimates to produce a fair value.

To provide an example of the disclosures made by firms about their fair value holdings, I present a table from PennyMac Mortgage Investment Trust's (trading symbol PMT) 2016 10-K in Appendix B. PMT had a large portfolio of fair value assets. In total, the firm reported total fair value assets valued on a recurring basis of $4.77 billion to a total asset base of $6.36 billion (not shown) and, thus, the majority of PMT's assets were fair value assets. As shown in the table, most of the fair value assets held by PMT were designated as Level 2 or Level 3 assets ($2.95 billion and $1.73 billion, respectively). For both the Level 2 and Level 3 fair value assets, the bulk of the holdings was in mortgage loans. As stated in their 10-K notes, PMT categorized mortgage loans that are not saleable into active markets as Level 3 fair value assets. These loans include substantially all of their distressed mortgage loans and mortgage loans acquired for sale which were subsequently repurchased pursuant to representations and warranties or that they identified as non-salable.

It is apparent that as the level of an asset increases, the amount of additional managerial input and estimates also increases. This can lead to situations where reported asset values in Level

2 and Level 3 assets may become inaccurate and opportunistically valued (Milbradt, 2011). For this reason, from an investor perspective, fair values based on unobservable inputs will have higher information risk relative to those based on observable inputs (Riedl and Serafiem, 2011). Moreover, the use of manager estimates for fair value estimates for Level 2 and Level 3 assets can create additional information asymmetries between the firm and investors and increase information processing costs for users of financial statements (McDonough et al., 2020).

2.3 Expectations

From the above discussion, prior literature suggests that more opaque assets may impose information risk on investors. I thus develop a one-sided hypothesis for how asset opacity in the financial sector is related to variance risk premiums and straddle returns. In short, I hypothesize that financial firms that have more opaque assets will have lower variance risk premiums and realized straddle returns.

I believe there are several not mutually exclusive reasons why we may observe this relationship. First, I assume that more opaque assets lead to low-quality reporting from firms and this in turn means investors have noisier valuation parameters (i.e., high information risk). Thus, higher information risk should raise total variances, systematic variance, and equity betas. Even if a Black-Scholes style model does not generate a variance risk premium for high volatility stocks, more volatile stocks likely have larger variance risk premiums empirically. Investors may attempt to hedge the higher-risk firm and dealers will have to raise option prices to protect themselves and generate an expected positive return on their trades.

Furthermore, higher levels of opaque assets may increase risks beyond expected variance. For example, more Level 2 and Level 3 assets may increase the likelihood, or perceived likelihood, of asset price crashes or jumps. In addition, information quality about fair value assets may drop in bad economic periods, precisely when better information is demanded. In the model of Mibradt (2011), asset opacity is related to negative skewness in observed accounting returns. Due to firms' choices to engage in trade in opaque markets, it can become advantageous not to trade when asset values drop. Thus, less reliable information is provided in bad states but, when losses are eventually recorded (realized or unrealized), the losses tend to be large compared to the gain recorded in better times. Thus, the asymmetries in reporting quality for gains and losses may lead to higher investor demand for option-based protections.

Finally, opaque assets may generate ambiguity for investors when attempting to value firms' stocks. As Epstein and Schneider (2008) explain, ambiguity is generated when signal quality is difficult to determine. This leads to a situation where investors have multiple valuation posteriors and each of the posteriors has a different variance component. When confronted with multiple variance possibilities, investors may trade acting on worst-case scenarios. This could lead investors to purchase options at relatively high prices relative to observed future variances.

Based on the above, my two (related) hypotheses for this study are as follows:

Hypothesis H1a: More opaque assets are negatively associated with variance risk premiums in the financial sector.

Hypothesis H1b: More opaque assets are negatively associated with straddle returns in the financial sector.

Again, as discussed above, I view realized variance risk premiums (i.e., the spread between IVs and realized volatilities) and straddle returns as proxies for the same underlying construct: more expensive option prices relative to subsequent equity variance. Thus, I do not view Hypothesis H1a and H1b as separate. Instead, in the upcoming tests, I look for consistency across my results.

I note that my hypotheses have tension. First, many of the prior studies that investigate the capital market effects of the fair value hierarchy look at the period around or immediately after the financial crisis of 2008. Thus, in more stable periods, it is not clear if opaque assets will affect the options market. In addition, except for Arora, Richardson, and Tuna (2014), empirical studies typically use a framework where asset opacity affects asset variances (e.g., Riedl and Serafiem, 2011). However, in theory, asset opacity must affect a higher-order risk to generate a variance risk premium. Finally, in many of my tests, I control for several other factors such as proxies of ex ante risk and option mispricing. Any relationship between asset opacity and variance risk premiums may be subsumed by these controls.

3. EMPIRICAL MODELS AND VARIABLE DEFINITIONS

To investigate the above questions, I use the following empirical models:

$$\begin{aligned} VRP_{it} \,/\, STRADDLE\_RET_{it} = {} & \alpha_1 LEVEL1AT_{it} + \alpha_2 LEVEL2AT_{it} + \alpha_3 LEVEL3AT_{it} + \alpha_4 LEVEL1LT_{it} + \\ & \alpha_5 LEVEL2LT_{it} + \alpha_6 LEVEL3LT_{it} + \alpha_7 LN\_MRKCAP_{it} + \alpha_8 LEV_{it} + \\ & \alpha_9 ROA_{it} + \alpha_{10} LOSS_{it} + \text{Month x Industry Fixed Effects} + \varepsilon_{it} \end{aligned} \tag{1}$$

$$\begin{aligned} VRP_{it} \,/\, STRADDLE\_RET_{it} = {} & \beta_1 LEVEL1AT_{it} + \beta_2 LEVEL2AT_{it} + \beta_3 LEVEL3AT_{it} + \beta_4 LEVEL1LT_{it} + \\ & \beta_5 LEVEL2LT_{it} + \beta_6 LEVEL3LT_{it} + \beta_7 LN\_MRKCAP_{it} + \beta_8 LEV_{it} + \\ & \beta_9 ROA_{it} + \beta_{10} LOSS_{it} + \beta_{11} LN\_IMPVOL_{it} + \beta_{12} IMPSKEW_{it} + \\ & \beta_{13} IMPCURVE_{it} + \text{Month x Industry Fixed Effects} + \xi_{it} \end{aligned} \tag{2}$$

$$\begin{aligned} VRP_{it} \,/\, STRADDLE\_RET_{it} = {} & \gamma_1 LEVEL1AT_{it} + \gamma_2 LEVEL2AT_{it} + \gamma_3 LEVEL3AT_{it} + \gamma_4 LEVEL1LT_{it} + \\ & \gamma_5 LEVEL2LT_{it} + \gamma_6 LEVEL3LT_{it} + \gamma_7 LN\_MRKCAP_{it} + \gamma_8 LEV_{it} + \\ & \gamma_9 ROA_{it} + \gamma_{10} LOSS_{it} + \gamma_{11} LN\_IMPVOL_{it} + \gamma_{12} IMPSKEW_{it} + \\ & \gamma_{13} IMPCURVE_{it} + \gamma_{14} LN\_SPREAD_{it} + \\ & \text{Month x Industry Fixed Effects} + \zeta_{it} \end{aligned} \tag{3}$$

In the above equations, I use two dependent variables. The first variable is *VRP*, defined as follows:

$$VRP_{it} = ln(\ RealizedVol_{it}[t + 1, t + 30] \,/\, IMPVOL_{it}\ )$$

In the above equation, *VRP* is defined as the log ratio of the annualized realized stock volatility using total daily log returns over the next 30 calendar days ($RealizedVol_{it}[t + 1, t + 30]$) to the 30-day ATM volatility (*IMPVOL*) calculated at the end of the calendar month t for firm i. I set *IMPVOL* to the mean of the 30-day 50 delta put and call IVs as provided by OptionMetrics.[7] Consistent with prior literature (e.g., Carr and Wu, 2009), I expect the average value of *VRP* to be negative. This would indicate that, on average, IVs are upward biased compared to future realized volatilities.[8]

The second dependent variable is *STRADDLE_RET* defined as the following:

$$STRADDLE\_RET_{it} = \frac{\max(K_{it,P} - S_{it+1}, 0) + \max(S_{it+1} - K_{it,C}, 0) - P_{it,P} - P_{it,C}}{P_{it,P} + P_{it,C}}$$

In the above equation, $K_{it,P}$ ($K_{it,C}$) is the 30-day 50 delta strike price of the put (call) at the end of month t using the OptionMetrics surface files and S_{it+1} is the stock price for firm i at the end of month $t + 1$. In addition, $P_{it,P}$ ($P_{it,C}$) is the price of the put (call) at the end of the month t for firm i. Thus, the maximum return to the straddle is unbounded but the maximum loss to the long straddle position is -100%.[9] Consistent with prior literature, I expect the average value of *STRADDLE_RET* to be negative, indicating that investors typically suffer losses when they purchase options.

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7 To be clear, the put delta is negative -0.50 and the call delta is 0.50. However, I refer the put and call deltas in absolute terms. Note that some studies use more complicated "model-free" implied volatilities (e.g., Neururer, Riedl, and Papadakis, 2016) but Smith and So (2022) suggest that the difference between model-free volatilities and ATM volatilities are small for short-dated option maturities.

8 This version of the variance risk premiums is similar to that used in other studies such as Carr and Wu (2009). In Carr and Wu (2009), they term my *VRP* variable as the "log variance risk premium". Some studies (e.g., Neururer, Papadakis, & Riedl, 2020) define variance risk premiums in the opposite way. In these cases, variance risk premiums are define as implied volatilities relative to realized volatility. My version of *VRP* should positively relate to my definition of a straddle return. In other words, when variance risk premiums are low, the associated straddle return should also be low.

9 The return to the call position is unbounded but the return to the put position is limited because the value of the stock cannot go below zero. Note that in the OptionMetrics surface files the strike prices for the 50 delta put and call are typically close to each other but will generally not be the same.

My main experimental variables are *LEVEL1AT*, *LEVEL2AT*, and *LEVEL3AT*. Again, I define the variables as the reported amount of Level 1, Level 2, and Level 3 assets reported by the firm scaled by total assets. To link the option data to Compustat, I use the earnings report date as provided by Compustat. Using the earnings report dates, I select the last quarterly data available at the time of the straddle position creation. Note that in my models the resulting coefficients for *LEVEL1AT*, *LEVEL2AT*, and *LEVEL3AT* are the associations of the fair value asset categories relative to the firm's non-fair value assets. Based on my hypotheses, I expect to estimate negative coefficients for *LEVEL2AT* and *LEVEL3AT*. However, for *LEVEL1AT*, I expect either near-zero or positive coefficients. I also expect the estimated coefficients for *LEVEL2AT* and *LEVEL3AT* to be more negative relative to the coefficients for *LEVEL1AT*.

In my multivariate tests, I control for several other factors. First, I define *LEVEL1LT*, *LEVEL2LT*, and *LEVEL3LT* as the book value of Level 1, Level 2, and Level 3 liabilities divided by book assets. Similar to the arguments for more opaque assets, it is possible that the estimated coefficients for *LEVE2LT* and *LEVEL3LT* will be negative. However, another possibility is that the estimated coefficients for the fair-value liability variables will be close to zero. Prior research has found that decision makers have trouble interpreting changes in value of fair-value liabilities (e.g., Bischof, Daske, and Sextroh, 2014). I also define *LN_MRKCAP* as the natural log of the market capitalization of the firm from the prior quarter. I do not sign my prediction for *LN_MRKCAP*. Larger firms will typically have greater systematic risks that may result in lower variance risk premiums (e.g., Barth and So, 2014) but prior research finds that idiosyncratic risks are priced in the option market (e.g., Cao and Han, 2013). I next define *LEV* as total book liabilities divided by book assets. Because greater leverage should increase risk, I predict a negative coefficient for *LEV*. I also define *ROA* as income before extraordinary items divided by book assets and *LOSS* as an indicator variable set to one if *ROA* < 0. Again, by risk arguments, I predict a negative coefficient for *LOSS* and a positive coefficient for *ROA*.

In Equation (2), I additionally add the market-implied risk variables *LN_IMPVOL*, *IMPSKEW*, and *IMPCURVE*. I define *LN_IMPVOL* as the natural log of *IMPVOL*. I define *IMPSKEW* as the natural log of the 30-day 20 delta call IV to the 30-day 20 delta put IV. Thus, *IMPSKEW* is a proxy for the option-implied return skew. I next define *IMPCURVE* as the natural log of the ratio of the mean of the 30-day 20 delta call IV and the 30-day 20 delta put IV to *IMPVOL*. In this case, *IMPCURVE* is a proxy for option-implied return kurtosis. When I use the option-implied risk measures in the model, the resulting coefficients on *LEVEL1AT*, *LEVEL2AT*, and *LEVEL3AT* provide information on how variance risk premiums and straddle returns are related by asset opacity beyond risk measures impounded into option prices.[10] In Equation (3), I add the variable *LN_SPREAD* defined as the natural log of the ratio of *IMPVOL* to the 91-day historical daily stock volatility. As shown by Goyal and Saretto (2009), straddle returns are lower for when the spread between IVs and historical volatilities are larger. Thus, I expect a negative coefficient for *LN_SPREAD* in the regression results. When controlling for *LN_SPREAD*, the regressions investigate if fair value asset variables are informative about variance risk premiums beyond spreads in historical volatilities and IVs.

Finally, I use month crossed with industry fixed effects in my regression models. This helps to control for industry shocks and adjusts the independent variables by month-industry averages. I define industries by three-digit SIC codes. Unless noted otherwise, I winsorize all variables at the 1st and 99th percentiles, standardized all continuous independent variables to have unit variance and a mean of zero, and I cluster all standard errors by month and by firm.

[10] See Bakshi, Kapadia, and Madan (2003) and Bakshi and Madan (2006) for more information on how skew and kurtosis are expected to influence variance risk premiums.

4. SAMPLE SELECTION AND SUMMARY STATISTICS

4.1 Sample construction

In Table 2, I detail the sample selection process. I collect options data on the last trading day of the month and retain observations where I was able to find data for 30-day ATM calls and puts and 20 delta calls and puts. I use the OptionMetrics surface files for the option data. As mentioned previously, I start the sample in 2009 because the fair value asset information becomes available in Compustat in 2008. The sample ends in 2017 because this is the limit to the data that I have available. This results in an initial data set with 397,857 observations for 5,963 firms.

I then remove 58,822 observations due to missing equity market data from CRSP. I then remove 51,082 observations because Compustat has missing data. This includes missing data for assets, liabilities, income before extraordinary items, shares outstanding, and end-of-quarter stock price. I also remove 823 observations because of a stock split or the stock was delisted during the month. I do this because this causes issues calculating the return to the straddle position. Next, to ensure the OptionMetrics and CRSP generally agree on the value of the underlying security, I remove an additional 1,603 observations because the absolute value of the log of the ATM strike price to CRSP stock price was more than 10%. Finally, I remove 229,428 non-financial observations (two-digit SIC code below 60 or above 67). My final sample has 56,099 observations representing 806 unique firms.

In Table 3, Panel A, I display the number of observations in the sample by year. Due to the increase in the number of firms with option coverage, my sample increases steadily throughout the examined period. In 2009, my sample has 4,771 observations representing 436 firms. In 2017, the final year of my sample, the number of observations increase to 7,456 representing 646 unique firms. Due to these trends, my results likely skew towards the end of the sample.

In Panel B of Table 4, I display the observations by financial sector, using two-digit SIC codes to define sectors. The two sectors with the largest representation are Holding and Other Investment Offices (two-digit SIC code = 67; N = 18,571) and Depository Institutions (two-digit SIC code = 60; N = 17,302). I also note that I have a large number of observations from Insurance Carriers (two-digit SIC code = 63; N = 9,363). On the other hand, I have relatively few observations from Insurance Agents, Brokers, and Service and Real Estate (two-digit SIC codes of 64 and 65 respectively). Thus, my results will tilt towards certain financial sectors.

4.2 Summary statistics

In Table 5, I display the summary statistics for the main sample. As expected, as consistent with prior literature, the mean and median values for *VRP* and *STRADDLE_RET* are negative. This indicates that, on average, the 30-day IVs extracted from option prices were upward biased and, moreover, investors suffered losses when they bought ATM straddles during the period. However, it should be noted that the period examined was relatively stable and the market did not suffer any large negative shocks. Untabulated results show that the average variance risk premium and straddle return was closer to zero for the calendar years 2007 and 2008. For example, the median *VRP* value for financial firms was -1.1% and 9.5% for 2007 and 2008, respectively.[11]

Consistent with the data in Table 1, the mean values for *LEVEL1AT*, *LEVEL2AT*, and *LEVEL3AT* are 4.6%, 16.9%, and 5.1%, respectively. Again, the statistics suggest that financial firms hold a large amount of fair value assets but the majority of financial firms' assets are not marked to market. In contrast, I find that financial firms hold relatively low values of fair value

[11] The median (mean) values for *STRADDLE_RET* in 2007 and 2008 are -29.6% and -19.8% (-7.3% and 1.8%), respectively.

liabilities. The mean values for Level 1, 2, and 3 liabilities scaled by assets (i.e., *LEVEL1LT*, *LEVEL2LT*, and *LEVEL3LT*) are 0.4%, 2.2%, and 1.2%, respectively.

The mean and median values for *LN_MRKCAP* are 7.66 and 7.51, respectively. Converting the median value, the value suggests the average firm in the sample as a market capitalization of \$1.83 billion (\$1,000,000 x *exp*(7.51)). Because of my need of options data, the sample skews towards larger firms, as expected. The mean (median) value for *LEV* is about 69% (76%). As expected, the average leverage values for financial firms are relatively high. I also find that the mean quarterly *ROA* is 0.8% and roughly 14% of the observations come from firms that reported a loss in the prior quarter. Finally, when examining the option-implied risk proxies, I find the mean (median) value for *IMPVOL* is 30.0% (36.5%). I also generate negative mean and median values for *IMPSKEW*. This indicates that the average firm in the sample has a negatively skewed option-implied return distribution. Moreover, I estimate a positive median value for *IMPCURVE*. This suggests that the median firm in the sample has anticipated excess return kurtosis. I however note that the mean value for *IMPCURVE* is actually slightly negative. Finally, I generate positive average values for *LN_SPREAD*. Somewhat consistent with the statistics for *VRP*, this indicates that IVs generally exceed historical volatilities.

5. RESULTS

5.1 Sample sorts

As a first test, I sort the observations on fair value assets and analyze the average *VRP* and *STRADDLE_RET* for the resulting quartiles. More specifically, I first sort the observations for each month-industry. I then fit the following regression model without an intercept:

$$VRP_{it} / STRADDLE\_RET_{it} = \delta_1 Q1_{it} + \delta_2 Q2_{it} + \delta_3 Q3_{it} + \delta_4 Q4_{it} + \varsigma_{it} \tag{4}$$

In (4), *Q1*, *Q2*, *Q3*, and *Q4* are indicator variables set to one if the observation has a value for the associated sorting measure in the first, second, third, or fourth quartile respectively within its month-industry. Table 5 displays the results.

In Panel A, I use *VRP* as the dependent variable and sort the observations using *LEVEL1AT* in column (1). The resulting coefficients suggest that as the amount of Level 1 assets increase, the values for *VRP* increase (i.e., become less negative). The coefficient for *Q1* is -0.265 (*t*-stat = 11.92) while the coefficient for *Q4* is -0.229 (*t*-stat = 11.21). However, an *F*-test shows that the difference in the coefficient for *Q4* and *Q1* are only significantly different at the 10% level using a two-sided test. In column (2) I sort using *LEVEL2AT*. For that sort, I do not observe a linear trend in the resulting coefficients. Instead, the coefficient *Q2* has the smallest estimated coefficient. However, the *F*-test suggests that the coefficients for *Q4* and *Q1* are again significantly different at the 10% level suggesting that firms with more Level 2 assets tend to have low variance risk premiums. In column (3), when using *LEVEL3AT* as the sorting variable, I do not generate a significant difference in the *Q4* and *Q1* coefficients. However, when combining the Level 2 and Level 3 assets to generate *LEVEL23AT* in column (4), I find the estimated coefficient for *Q4* is significantly smaller than the estimated coefficient for *Q1* at the 5% level. The difference in the coefficients suggests that firms in the top quartile of opaque assets, on average, and lower variance risk premiums by about 4% relative to those in the lowest quartile.

I repeat the analysis in Panel B when using *STRADDLE_RET* as the dependent variable. The results are generally consistent with those in Panel B. I find evidence that those firms with high levels of Level 2 assets and those firms with high levels of total opaque assets (i.e., *LEVEL23AT*) tend to have lower straddle returns compared to firms with fewer opaque assets. Again, the column (4) results suggests that firms in the top quartile of opaque assets, on average, and lower straddle returns by about 4.4% relative to those in the lowest quartile of opaque assets. One noticeable difference between the Panel B and Panel A results is that I do not estimate a significant difference between the coefficients for *Q4* and *Q1* in Panel B when using *LEVEL1AT* as the sorting variable (column (1)). Still, the results of this section provide some initial evidence that amount of fair value assets held in the Level 1, 2, and 3 categories by financial firms helps to explain variance risk premiums.

5.2 Multivariate results

I next investigate the impact of asset opacity on variance risk premiums and straddle returns using multivariate regressions. I start by using *VRP* as the dependent variable. I display the results in Table 6.

In column (1), I use the three fair value asset variables along with month fixed effects. I estimate a positive and significant coefficient for *LEVEL1AT* (*t*-stat = 3.40). The estimated coefficient suggests that a one-standard deviation increase in Level 1 fair assets on the balance sheet is associated with an increase in variance risk premiums by 1.9%.[12] I also find a significant negative coefficient for *LEVEL3AT* (*t*-stat = 4.99). The estimated coefficient suggests that a one-standard deviation increase in Level 3 fair assets would decrease *VRP* by about 4.5%. Thus, it appears that the level of balance sheet asset opacity has an economically meaningful impact on option prices. I do not estimate a significant coefficient for *LEVEL2AT*. However, the estimated coefficients for the variables are decreasing as the opacity increase. An untabulated *F*-test also shows that the estimated coefficients for *LEVEL1AT* and *LEVEL3AT* are significantly different from each other at the 1% level, two-sided test.

[12] Again, as the regression results hold the other variables constant in the analysis, implicitly increasing Level 1 assets means simultaneously decreasing other non-fair value assets.

In column (2), I replace the month fixed effects with month-industry fixed effects. The resulting coefficient for *LEVEL3AT* is qualitatively unaffected by this change. This suggests that the negative association between the amount of Level 3 assets held by firms and variance risk premiums is not explained by industry shocks during the period, nor is it explained by the variation of Level 3 assets held across industries. However, the switch in fixed effects causes the estimated coefficient for *LEVEL1AT* to become insignificant (*t*-stat = 0.91). This indicates that the negative association presented in column (1) is likely due to industry-level variation in the holdings of Level 1 assets. Those industries within financials that hold more Level 1 assets tend to have higher variance risk premiums. However, when controlling for industry membership in column (2), the negative association is subsumed by the fixed effects.

In column (3), I add the fair value liability variables to the model (*LEVEL1LT*, *LEVEL2LT*, and *LEVEL3LT*). I do not estimate significant coefficients for any of the fair value liability variables. However, I continue to estimate a negative and significant variable for *LEVE3AT*. I next add the firm variables *LN_MRKCAP*, *LEV*, *ROA*, and *LOSS* in column (4). The inclusion of the additional variables does not eliminate the negative association between the amount of Level 3 assets and variance risk premiums. Instead, the coefficient on *LEVEL3AT* remains significant at traditional levels.

I then add the option-implied risk variables in column (5). As expected, I estimate a strong negative coefficient for *LN_IMPVOL* (*t*-stat = 29.62). This indicates that financial firms with high anticipated future variance typically also have lower (more negative) levels of variance risk premiums. I also estimate a positive coefficient for *IMPSKEW* (*t*-stat = 4.41) and a negative coefficient for *IMPCURVE* (*t*-stat = 4.32). However, the inclusion of these variables does not qualitatively affect the strong negative association between *LEVEL3AT* and *VRP*. Conditional on the option-implied risk measures and other controls, the estimated coefficient for *LEVEL3AT* suggests that a one-standard deviation increase in Level 3 fair assets would decrease *VRP* by about 3.4% (*t*-stat = 4.73). Interestingly, I also now estimate a negative and significant coefficient for *LEVEL2AT* (*t*-stat = 2.45). Again, conditional on the option-implied risks, I now find evidence that more Level 2 and Level 3 assets are associated with lower variance risk premiums. Finally, in column (6), I add *LN_SPREAD* as an additional control. As previously discussed, prior literature finds the spread between historical volatilities and IVs is valuable for explaining variance risk premiums. I estimate a strong negative coefficient for *LN_SPREAD* in the models (*t*-stat = 49.27), as expected. I do not, however, find the inclusion of *LN_SPREAD* materially alters the coefficients for *LEVEL2AT* and *LEVEL3AT*. Thus, the level of asset opacity appears to explain variance risk premiums in financials even after adjusting for a proxy of option mispricing.

In Table 7, I repeat the analyses of Table 6 when replacing *VRP* as the dependent variable with *STRADDLE_RET*. Overall, the results of Table 7 are similar to those in Table 6. In column (1), when only using month fixed effects, I estimate a significant negative (positive) coefficient for *LEVEL3AT* (*LEVEL1AT*). When I incorporate the month-industry fixed effects and other firm-level factors in columns (2) – (4), I instead only estimate a significant negative coefficient for *LEVEL3AT* only. When I add the option-implied risk controls in column (5), I continue to estimate a negative association between Level 3 assets and straddle returns, but I also estimate a negative and significant coefficient for *LEVEL2AT*. Only in column (6) do I generate a qualitatively different result compared to that of Table 5; I estimate a negative but insignificant coefficient for *LEVEL2AT* (*t*-stat = 1.57).

In summary, the results of this section provide evidence that asset opacity is associated with variance risk premiums and straddle returns for financial firms. I find consistent evidence that firms with more Level 3 assets tend to have lower variance risk premiums. I also find some evidence that, after controlling for option-implied risks, greater amounts of Level 2 assets are also negatively related to variance risk premiums.

5.3 Sample splits by firm size

As an additional test, I examine if my results are confined to smaller firms. Small firms typically have less analyst and media attention and, thus, have less developed information environments (e.g., Riedl and Serafeim 2011). Because I hypothesize that more opaque assets generate higher information risk, the negative relationship between variance risk premiums and opaque assets may be limited to instances where other information intermediaries do not mitigate the additional risk.

For these tests, I first split the sample using intra-month-industries. I select observations with total assets smaller than or equal to their respective month-industry median to create a small firm subsample. The remaining observations comprise the large firm subsample. Table 8 displays the regression results using the two subsamples when *VRP* is set to the dependent variable.

In column (1), I show the regression results for the small firm observations with the full set of controls, save *LN_SPREAD*. I estimate a strong negative coefficient for *LEVEL3AT* (*t*-stat = 5.06) suggesting that for small firms, the amount of opaque assets increases the spread between realized and IVs. The coefficient for *LEVEL3AT* suggests a one-standard deviation increase in Level 3 assets decreases variance risk premiums by 5.4%. Conversely, I do not estimate significant coefficients for *LEVEL1AT* and *LEVEL2AT*. In column (2), I add *LN_SPREAD* as an additional control. The estimated coefficient for *LEVEL3AT* is cut in half relative to the value estimated in column (1). However, the estimated coefficient remains highly significant (*t*-stat = 4.14).

In column (3), I use the large firm observations when excluding *LN_SPREAD* as a control. In contrast to the small firm results, I estimate a negative and significant coefficient for *LEVEL2AT* (*t*-stat = 2.85) and a negative but insignificant coefficient for *LEVEL3AT*. Thus, it appears that asset opacity is related to variance risk premiums even for larger firms, but the type of the assets that generate the relationship differs for larger versus small firms. In addition, the negative association between *LEVEL2AT* and *VRP* holds in column (4) when I add *LN_SPREAD* as a control. Moreover, I estimate a negative and weakly significant coefficient for *LEVEL3AT* (*t*-stat = 1.76). In short, asset opacity seems to affect variance risk premiums for both large and small firms, but the precise source of the relationship is somewhat different for the two firm types. This could be due to the average holdings differing across the two firm size subsamples. More specifically, untabulated results show that the mean *LEVEL2AT* and *LEVEL3AT* values for the small firm observations are 15.7% and 6.8%, respectively. In constrast, for the large firm observations, the mean *LEVEL2AT* and *LEVEL3AT* values are 18.2% and 3.4%, respectively.

5.4 Sample splits by year

I next investigate if my results are primarily due to the years that immediately followed the financial and stock market crash of 2008. Due to the large shock to the financial sector, investors may have been wary of firms that held large amounts of opaque assets in the post-collapse period. However, when conditions improved over the next decade, investor fears about asset opacity may have subsided thus reducing or eliminating the association between variance risk premiums and asset opacity levels.

I consequently split the sample into three subsamples: observations for the years 2009 to 2011, 2012 to 2014, and 2015 to 2017. I then re-estimate regressions for the subsamples when controlling for the firm-level factors and option-implied risk measures. I also re-estimate the regressions when *LN_SPREAD* is added as a control. Table 9 displays the results.

In columns (1) and (2), I show the results for the first three years. In general, the results for the fair value assets are weak. I estimate negative and significant coefficients for *LEVEL2AT*. However, the resulting coefficients are not large economically or statistically. In addition, I do not estimate significant coefficients for *LEVEL3AT*. Thus, I conclude that the main results are not due to the years after the financial crisis. In columns (3) and (4), I display the results for the years 2012 to 2014. For these years, the estimated coefficients for *LEVEL3AT* are negative and significant. Again, however, the economic magnitude of the coefficients is limited.

Finally, in columns (5) and (6), I display the results for the final three years of the sample. For these years, I estimate large negative and statistically significant coefficients for *LEVEL2AT* and *LEVEL3AT*. When I do not use *LN_SPREAD* as a control in column (5), the resulting coefficient for *LEVEL2AT* suggests that a one-standard deviation increase in Level 2 assets was associated with a drop of 3.5% (*t*-stat = 4.05) in variance risk premiums. Moreover, the coefficient for *LEVEL3AT* indicates that a one-standard deviation increase in Level 3 assets was associated with a drop of 6.2% (*t*-stat = 5.76) in variance risk premiums during the later years.

There are at least two explanations for these findings. First, it is possible that investors became more aware and concerned with asset opacity during the sample period, leading to a stronger association between firms' asset opacity levels and the demand for long option positions. In addition, because more firms were covered by options later in the sample, the results of Table 9 may be due to shifts in the sample coverage. In other words, the documented increase in coefficients for *LEVEL2AT* and *LEVEL3AT* in the later years is caused by the inclusion of new firms into the sample that did not have equity options trading in the earlier years.

5.5 Robustness tests

I subject the results to a series of robustness tests. I focus these tests on the main results as presented in Tables 6 and 7.

First, I attempt to address the issue of outliers and non-linearities affecting the results. The dependent variables *VRP* and *STRADDLE_RET*, even after winsorization, may still have outlier issues that affect the reported results. These issues may also be present for the fair value variables. Consequently, I convert all the variables to percentile ranks. The use of ranks helps to eliminate issues of outliers by re-scaling the data and provides an easy way to check for robustness while allowing for a large number of fixed effects. I display the regressions using ranks in Table 10. In columns (1) and (2), I find that *LEVEL3AT* is still negative and significant when using *VRP* as the dependent variable. Moreover, in column (2), I find evidence that both *LEVEL2AT* and *LEVEL3AT* are significantly and negatively associated with *STRADDLE_RET*. Thus, the use of ranks does affect the tenor of the results.

As a second test, I incorporate the monthly equity return into the analysis. It is possible that firms with higher levels of opaque assets had higher stock returns during the period. Thus, the prior results may have been due to signed equity returns and not differences in variance risk premiums, per se. However, in untabulated results, I find that the results are qualitatively unchanged when I add the monthly equity returns as a control variable to the regression models. I continue to find evidence that *LEVEL3AT* is consistently negatively related to the main dependent variables and, for some regression specifications, I estimate significant negative coefficients for *LEVEL2AT* as well. I also find the results are robust to including, as additional independent variables, firms' book-to-market ratios and an indicator variable set to one if the firm paid a dividend in the prior quarter.

Finally, I replace the month-industry fixed effects with month and firm fixed effects to remove static firm-level heterogeneity. I find that the prior results do *not* hold (untabulated). In particular, the estimated coefficients for *LEVEL2AT* and *LEVEL3AT* are no longer significant for the main regression models. There are two potential reasons for this. First, firm holdings of fair value assets are very sticky and the use of firm fixed effects may remove too much variation in the variables. For example, the regression R^2's are 80.2%, 92.5%, and 92.6% when using firm fixed effects and setting the dependent variable to *LEVEL1AT*, *LEVEL2AT*, and *LEVEL3AT*, respectively. However, an alternative explanation is that the prior results are due to omitted variables at the firm level. I cannot rule out that possibility.

5.6 Skew trading returns

I also examine if asset opaqacity is associated with skew trading returns and if the prior results regarding variance risk premiums hold when controlling for skew premiums. To generate a skew return, I follow Bali and Murray (2013) and calculate the monthly return to delta-neutral risk reversal positions. I purchase one 30-day 20 delta put and sell *X* units of the 30-day 20 delta call on the same dates as the straddle positions. Here, *X* is chosen to make the position vega neutral. I then buy enough stock shares to make the position delta neutral. I finally calculate the profit of the position at the end of the month and scale the profit by the capital necessary to create the position to generate a proxy for skew premiums.

I then replace *VRP* with the skew return as the dependent variable in Table 6. In untabulated results, I do not find evidence that *LEVEL2AT* or *LEVEL3AT* are associated with skew returns. Thus, it appears that asset opacity does not affect the excess demand of OTM puts to calls. In addition, I add the skew returns as an independent variable in the Tables 6 and 7 regressions. Untabulated results again show that *LEVEL3AT* is consistently and negatively associated with *VRP* and *STRADDLE_RET* even when controlling for concurrent skew returns. I also find that the coefficient on *LEVEL2AT* is, at times, significant and negative in Tables 6 and 7 with the additional control variable. I thus conclude the main results are not due to changes in skew premiums.

5.7 Implied volatility precision

As a final test, I investigate if asset opacity is associated with IV forecast precision. In other words, I test if IVs are a better or worse predictor of future return volatilities when a firm has higher levels of opaque assets. I thus replace signed *VRP* with the absolute value of the *VRP* (*ABS_VRP*) as the regression dependent variable. Table 11 shows the results.

In column (1), I use the fundamental factors as the independent variables. I find that *LEVEL3AT* is positive and significant (*t*-stat = 3.98). This suggests that IVs are worse predictors of future volatility when a firms has more Level 3 assets. However, I estimate insignificant coefficients for *LEVEL1AT* and *LEVEL2AT*. In column (2), I control for the option-implied risks. I know estimate positive and significant coefficients for both *LEVEL2AT* and *LEVEL3AT*. Thus, conditional on the option-implied risks, I find for opaque assets reduce the precision of IVs for predicting future volatility. In column (3) I find that controlling for *LN_SPREAD* does not alter this finding.

In columns (4) – (6), I additionally consider that the forecasting precison of IVs may be related to the signed *VRP*. I thus control for *VRP* in the regressions. Across the three regressions, I find *VRP* is negatively related to *ABS_VRP*, as expected. However, the tenor of the asset opacity results are unaffected by the inclusion of *VRP* as a control. Instead, I continue to find evidence that Level 3 assets, and to a lesser extent Level 2 assets, reduce the forecasting power of IVs for future realized volatility.[13]

[13] The results of Table 11 hold when, as a proxy for option market liquidity, I include the log of option interest as a control. As expected, the regression coefficients for log of open interest are negative and significant, suggesting

6. CONCLUSIONS

In this study, I examine the association between asset opacity and variance risk premiums. I focus on financial firms due to their relatively high holdings of fair value assets and because their equity values are more closely tied to book equity values compared to other economic sectors. Due to the information risk opaque asset possess, I hypothesize that firms with more opaque fair value assets relative to their book assets will have lower variance risk premiums and lower straddle returns. I operationalize opaque fair value assets as those designated as Level 2 and Level 3 assets and transparent fair value assets as those with a Level 1 designation.

My results suggest that firms with more opaque assets have significantly lower variance risk premiums and straddle returns. More specifically, I find consistent evidence that firms with high levels of Level 3 assets tend to have lower straddle returns and a larger spread between future realized volatility and current IVs. This result holds after controlling for several firm-level factors, implied-option risks, and proxies for option misevaluation. I also present, albeit weak, evidence that firms with greater amounts of Level 2 assets have lower variance risk premiums after controlling for option-implied risk measures. Further tests show that the negative association between Level 3 assets and variance risk premiums is strongest in smaller firms, and the negative relationship between Level 2 assets and variance risk premiums is confined to larger firms. Finally, I show that the main results are not due to observations in the years immediately following the financial crisis of 2008. Instead, the negative association between asset opacity and variance risk premiums is strongest in the later years of the sample.

In short, I find that financial firms with higher asset opacity tend to have lower variance risk premiums and straddle returns. The results point to higher information risk generating excess

that IVs from more liquid markets are better predictors of future realized volatility. For these tests, I only consider observations where the open interest was greater than zero (N = 55,145).

demand for option-based protections. However, I note several caveats to the results. First, the results do not establish causality between the variables. However, the amount of opaque assets held by firms is sticky and, thus, firm fixed effects likely remove too much variance in the fair value assets. In addition, the results imply but do not test a trading strategy. Transaction costs may potentially eliminate any profits from a long-short type of strategy suggested by the results. However, the results should be useful to investors that use IVs to forecast volatility and control for risk in their portfolios. In addition, the results should be of interest to other research by showing that there appears to be a connection between information risk (as proxied by asset opacity) and variance risk premiums for financial firms.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from Compustat, CRSP, and OptionMetrics as of the download dates in November 2018. Restrictions apply to the availability of the data sets, which were used under license for this study. The data set used is available with the permission of the above data vendors.

References

Arora, N., Richardson, S., & Tuna, I. (2014). Asset reliability and security prices: evidence from credit markets. *Review of Accounting Studies, 19*, 363-395.
https://doi.org/10.1007/s11142-013-9254-7

Ayres, D. (2016). Fair value disclosures of level three assets and credit ratings. *Journal of Accounting and Public Policy, 35*, 635-653.
https://doi.org/10.1016/j.jaccpubpol.2016.08.002

Bakshi, G., & Kapadia, N. (2003). Delta-hedged gains and the negative market volatility risk premium. *Review of Financial Studies, 16*, 527-566.
https://doi.org/10.1093/rfs/hhg002

Bakshi, G., Kapadia, N., & Madan, D. (2003). Stock return characteristics, skew laws, and the differential pricing of individual equity options. *Review of Financial Studies, 16*, 101-143.
https://doi.org/10.1093/rfs/16.1.0101

Bakshi, G., & Madan, D. (2006). A theory of volatility spreads. *Management Science*, *52*, 1945-1956.
https//doi.org/10.1287/mnsc.1060.0579

Bali, T., & Murray, S. (2013) Does risk-neutral skewness predict the cross-section of equity option portfolio returns? *Journal of Financial and Quantitative Analysis*, *48*, 1145-1171.
https://doi.org/10.1017/S0022109013000410

Barth, M., & So, E. (2014). Non-diversifiable volatility risk and risk premiums at earnings announcements. *The Accounting Review*, *89*, 1579–1607.
https://doi.org/10.2308/accr-50758

Bates, D. (1996). Jumps and stochastic volatility: Exchange rate processes implicit in Deutsche Mark options. *Review of Financial Studies, 9*, 69-107.
https://doi.org/10.1093/rfs/9.1.69

Bischof, J., Daske, H., & Sextroh, C. (2014). Fair value-related information in analysts' decision processes: Evidence from the financial crisis. *Journal of Business, Finance, & Accounting*, *41*, 363-400.
https://doi.org/10.1111/jbfa.12063

Black, F., & Scholes, M. (1973). The pricing of options and corporate liabilities. *Journal of Political Economy, 81*, 637-654.
https://doi.org/10.1086/260062

Broadie, M., Chernov, M., & Johannes, M. (2007). Model specification and risk premia: Evidence from futures options. *Journal of Finance*, *62*, 1453-1490.
https://doi.org/10.1111/j.1540-6261.2007.01241.x

Buss, A., & Vilkov, G. (2012). Measuring equity risk with option-implied correlations. *Review of Financial Studies*, *25*, 3113-3140.
https://doi.org/10.1093/rfs/hhs087

Cao, J., & Han, B. (2013). Cross section of option returns and idiosyncratic stock volatility. *Journal of Financial Economics*, *108,* 231–249.
https://doi.org/10.1016/j.jfineco.2012.11.010

Carr, P., & Wu, L. (2009). Variance risk premiums. *Review of Financial Studies*, *22*, 1311-1341.
https://doi.org/10.1093/rfs/hhn038

Culp, C., Nozawa, Y., & Veronesi, P. (2018). Option-based credit spreads. *American Economic Review*, *108*, 454-488.
https://doi.org/10.1257/aer.20151606

DeMiguel, V., Plyakha, Y., Uppal, R., & Vilkov, G. (2013). Improving portfolio selection using option-implied volatility and skewness. *Journal of Financial and Quantitative Analysis*, *48*, 1813-1845.
https://doi.org/10.1017/S0022109013000616

Driessen, J., Maenhout, P., & Vilkov, G. The price of correlation risk: Evidence from equity options. *Journal of Finance*, *64*, 1377-1406.
https://doi.org/10.1111/j.1540-6261.2009.01467.x

Duffie, D., & Lando, D. (2001). Term structures of credit spreads with incomplete accounting information. *Econometrica*, *69*, 633-664.
https://doi.org/10.1111/1468-0262.00208

Epstein, L., & Li, S. 2013. Ambiguous volatility and asset pricing continuous time. *Review of Financial Studies*, *26*, 1740-1786.
https://doi.org/10.1093/rfs/hht018

Epstein, L., & Schneider, M. (2008). Ambiguity, information quality, and asset pricing. *Journal of Finance*, *63*, 197-228.
https://doi.org/10.1111/j.1540-6261.2008.01314.x

Heston, S. (1993). A closed-form solution for options with stochastic volatility with applications to bond and currency options. *Review of Financial Studies*, *6*, 327–343.
https://doi.org/10.1093/rfs/6.2.327

Financial Accounting Standards Board (FASB). (2006). Fair Value Measurements. Statement of Financial Accounting Standards No. 157. Norwalk, CT. FASB.

Financial Accounting Standards Board (FASB). (2011). Fair Value Measurement. Accounting Standards Codification 820. Norwalk, CT: FASB.

Gârleanu, N., Pedersen, L., & Poteshman, (2009). Demand-based option pricing. *Review of Financial Studies*, *22*, 4259-4299.
https://doi.org/10.1093/rfs/hhp005

Goyal, A., & Saretto, A. (2009). Cross-section of option returns and volatility. *Journal of Financial Economics*, *94*, 310–326.
https://doi.org/10.1016/j.jfineco.2009.01.001

Kolev, K. (2019). Do investors perceive marking-to-model as marking-to-myth? Early evidence from FAS 157 disclosure. *Quarterly Journal of Finance*, *9*, 1950005.
https://doi.org/10.1142/S2010139219500058

Lambert, R., Leuz, C., & Verrecchia, R. (2007). Accounting information, disclosure, and the cost of capital. *Journal of Accounting Research*, *45*, 385-420.
https://doi.org/10.1111/j.1475-679X.2007.00238.x

Lawrence, A., Siriviriyakul, S., & Sloan, R. (2016). Who's the fairest of them all? Evidence from closed-end funds. *The Accounting Review*, *91*, 207-227.
http://doi.org/10.2308/accr-51152

McDonough, R., Panaretou, A., & Shakespeare, C. (2020). Fair value accounting: Current practice and perspectives for future research. *Journal of Business Finance and Accounting*, *47*, 303-332.
https://doi.org/10.1111/jbfa.12447

Milbradt, K. (2012). Level 3 assets: Booking profits and concealing losses. *Review of Financial Studies*, *25*, 55-95.
https://doi.org/10.1093/rfs/hhr112

Neururer, T., Papadakis, G., & Riedl, E. (2016). Tests of investor learning models using earnings innovations and implied volatilities. *Review of Accounting Studies*, *21*, 400–437.
https://doi.org/10.1007/s11142-015-9348-5

Neururer, T., Papadakis, G., & Riedl, E. (2020). The effect of reporting streaks on ex ante uncertainty. *Management Science*, *66*, 3295-3798.
https://doi.org/10.1287/mnsc.2019.3320

Nissim, D. (2013) Relative valuation of U.S. insurance companies. *Review of Accounting Studies*, *18*, 324-359.
https://doi.org/10.1007/s11142-012-9213-8

Riedl, E., & Serafeim, G. (2011). Information risk and fair values: An examination of equity betas. *Journal of Accounting Research*, *49*, 1083-1122.
https://doi.org/10.1111/j.1475-679X.2011.00408.x

Smith, K., & So, E. (2022). Measuring risk information. *Journal of Accounting Research*, *60*, 375-426.
https://doi.org/10.1111/1475-679X.12413

Song, C.J., Thomas, W., & Yi, H. (2010). Value relevance of FAS No. 157 fair value hierarchy information and the impact of corporate governance mechanisms. *The Accounting Review*, *85*, 1375-1410.
http://doi.org/10.2308/accr.2010.85.4.1375

[dataset] Compustat Industrial [Quarterly Data]. (1995-2017). Available: Standard & Poor's/Compustat [November 2018]. Retrieved from Wharton Research Data Service.

[dataset] CRSP Stocks. (1995-2017). Available: Center For Research in Security Prices. Graduate School of Business. University of Chicago [November 2018]. Retrieved from Wharton Research Data Service.

[dataset] Ivy DB Optionmetrics (1996-2017). Available: Ivy DB Optionmetrics [November 2018]. Retrieved from Wharton Research Data Service.

APPENDIX A: VARIABLE DEFINITIONS

Dependent Variables

VRP *(ABS_VRP)*	The (absolute value of the) log ratio of the annualized realized volatility of dividend-adjusted log equity returns over the next 30 calendar days to the ATM 30-day implied volatility. The ATM implied volatility is the mean of the 50 delta put and call from the OptionMetrics volatility surface files taken on the last trading day of the calendar month.
STRADDLE_RET	The monthly ATM straddle return. The position is long the 50 delta put and call using closing prices on the last trading day of the month. The return is the value of the put or call at the end of the month (based on the ending stock price) minus the initial value of the straddle divided by the initial value of the straddle. The initial put and call prices are taken from OptionMetrics volatility surface files and stock prices are from the CRSP monthly files.

Other Variables

LEVEL1AT (*LEVEL2AT*) [*LEVEL3AT*]	The value of Level 1 (Level 2) [Level 3] assets scaled by total reported assets from the last quarterly report. Data from Compustat.
LEVEL1LT (*LEVEL2LT*) [*LEVEL3LT*]	The value of Level 1 (Level 2) [Level 3] liabilities scaled by total reported assets from the last quarterly report. Data from Compustat.
LEVEL23AT	The value of Level 2 assets plus Level 3 assets scaled by total reported assets from the last quarterly report. Data from Compustat.
FVAT	Total fair value assets divided by total reported assets from the last quarterly report. Data from Compustat.
MRKCAP *(LN_MRKCAP)*	The (natural log of the) firm's market capitalization in millions of dollars from the end of the prior quarter. Data from Compustat.
LEV	The ratio of total liabilities to total assets from the last quarterly report. Data from Compustat.
ROA	The ratio of income before extraordinary items to total assets from the last quarterly report. Data from Compustat.
LOSS	An indicator variable set to one if *ROA* < 0 and zero otherwise.
IMPVOL *(LN_IMPVOL)*	The (natural log of the) 30-day ATM volatility. The ATM volatility is the same value used in defining *VRP*.
IMPSKEW	The natural log of the ratio of the 30-day 20 delta implied call volatility to the 30-day 20 delta implied put volatility. The put and call prices implied volatilities are taken from OptionMetric volatility surface files.
IMPCURVE	The natural log of the ratio of the average of the 30-day OTM volatilities to *IMPVOL*. The OTM volatilities are the 30-day 20 delta implied call volatility and the 30-day 20 delta implied put volatility. The implied volatilities are taken from OptionMetric volatility surface files.
LN_SPREAD	The natural log of the ratio of *IMPVOL* to the historical 90-day stock volatility. Stock return volatility from CRSP.

APPENDIX B: EXAMPLE DISCLOSURE

	December 31, 2016			
	Level 1	Level 2	Level 3	Total
	(in thousands)			
Assets:				
Short-term investments	$ 122,088	$ —	$ —	$ 122,088
Mortgage-backed securities at fair value	—	865,061	—	865,061
Mortgage loans acquired for sale at fair value	—	1,673,112	—	1,673,112
Mortgage loans at fair value	—	367,169	1,354,572	1,721,741
Excess servicing spread purchased from PFSI	—	—	288,669	288,669
Derivative assets:				
Interest rate lock commitments	—	—	7,069	7,069
CRT Agreements	—	—	15,610	15,610
MBS put options	—	1,697	—	1,697
MBS call options		142	—	142
Forward purchase contracts	—	30,879	—	30,879
Forward sales contracts	—	13,164	—	13,164
Put options on interest rate futures	2,469	—	—	2,469
Call options on interest rate futures	63	—	—	63
Total derivative assets before netting	2,532	45,882	22,679	71,093
Netting	—	—	—	(37,384)
Total derivative assets after netting	2,532	45,882	22,679	33,709
Mortgage servicing rights at fair value	—	—	64,136	64,136
	$ 124,620	$ 2,951,224	$ 1,730,056	$ 4,768,516
Liabilities:				
Asset-backed financing of a VIE at fair value	$ —	$ 353,898	$ —	$ 353,898
Interest-only security payable at fair value	—	—	4,114	4,114
Derivative liabilities:				
Interest rate lock commitments	—	—	3,292	3,292
Forward purchase contracts	—	7,619	—	7,619
Forward sales contracts	—	17,974	—	17,974
Put options on interest rate futures	—	—	—	—
Total derivative liabilities before netting	—	25,593	3,292	28,885
Netting	—	—	—	(19,312)
Total derivative liabilities after netting	—	25,593	3,292	9,573
	$ —	$ 379,491	$ 7,406	$ 367,585

Note: The above figure displays the fair value information for PennyMac Mortgage Investment Trust (trading symbol PMT; CUSIP 70931T10; CIK #0001464423). The table is take from PMT's 2016 10-K.

TABLE 1 Fair value assets – financial versus non-financial firms

	N	*FVAT*	*LEVEL1AT*	*LEVEL2AT*	*LEVEL3AT*
Financials	56,099				
Mean		26.1%	4.6%	16.9%	5.1%
Median		14.0%	0.1%	7.1%	0.0%
Non-financials	229,428				
Mean		10.5%	5.6%	4.5%	0.2%
Median		0.6%	0.0%	0.0%	0.0%

Note: This table displays the summary statistics for fair value assets for the financial and non-financial observations from 2009 – 2017. Financial firms have two-digit SIC codes between 60 and 67. *FVAT*, *LEVEL1AT*, *LEVEL2AT*, and *LEVEL3AT* are the total fair value assets, Level 1 assets, Level 2 assets, and Level 3 assets scaled by total book asset respectively. Values are displayed after winsorizing the variables at the 1st and 99th percentiles. See Table 2 for the sample construction process.

TABLE 2 Sample selection

	Observations Lost	Observations	Unique Firms
Monthly option observations (2009 - 2017)		397,857	5,963
(-) Missing CRSP data	-58,822	339,035	5,094
(-) Missing Compustat data	-51,082	287,953	4,303
(-) Stock split or delisted	-823	287,130	4,303
(-) Stock and at-the-money strike prices too different	-1,603	285,527	4,301
(-) Non-financial firms	-229,428	56,099	806

Note: This table displays the sample selection process. Financial firms have two-digit SIC codes between 60 and 67. At-the-money (ATM) strike prices are calculated by taking the mean of the 50 delta 30-day put and call strike prices. Observations are removed if the absolute value of the log ratio of the stock price to the ATM strike price is more than 10%.

TABLE 3 Sample information

Panel A: Observation counts by year

Year	Observations	Unique Firms
2009	4,771	436
2010	4,954	447
2011	5,379	504
2012	5,762	526
2013	6,280	569
2014	6,740	592
2015	6,973	685
2016	7,784	683
2017	7,456	646

Panel B: Observation counts by two-digit SIC codes

Description	Two-digit SIC Code	Observations	Unique Firms
Depository Institutions	60	17,302	274
Non-depository Institutions	61	2,737	43
Security and Commodity Brokers	62	5,898	81
Insurance Carriers	63	9,363	120
Insurance Agents, Brokers, and Service	64	1,077	16
Real Estate	65	1,151	19
Holding and Other Investment Offices	67	18,571	253

Note: This table displays observation codes by year and two-digit SIC codes. Panel A displays the number of observations and unique firms by year. Panel B displays the number of observations and unique firms by their two-digit SIC codes.

TABLE 4 Summary statistics

	P25	P50	Mean	P75	Std. Dev.
VRP	-46.9%	-20.8%	-24.9%	2.9%	44.7%
STRADDLE_RET	-72.7%	-38.6%	-21.6%	11.8%	66.4%
LEVEL1AT	0.0%	0.1%	4.6%	4.0%	9.9%
LEVEL2AT	0.0%	7.1%	16.9%	24.9%	22.6%
LEVEL3AT	0.0%	0.0%	5.1%	0.7%	18.0%
LEVEL1LT	0.0%	0.0%	0.4%	0.0%	2.0%
LEVEL2LT	0.0%	0.0%	2.2%	0.2%	8.7%
LEVEL3LT	0.0%	0.0%	1.2%	0.0%	5.8%
LN_MRKCAP	6.56	7.51	7.66	8.55	1.58
LEV	52.5%	75.5%	68.6%	88.6%	23.9%
ROA	0.1%	0.3%	0.8%	0.9%	2.0%
LOSS	0.0%	0.0%	14.1%	0.0%	34.8%
IMPVOL	22.7%	30.0%	36.5%	42.9%	21.0%
IMPSKEW	-35.7%	-23.1%	-20.4%	-7.3%	30.9%
IMPCURVE	-59.0%	5.7%	-0.8%	63.4%	93.8%
LN_SPREAD	-6.3%	11.1%	17.0%	32.6%	38.9%

Note: This table displays the summary statistics for the sample. P25, P50, and P75 are the values at the 25^{th}, 50^{th}, and 75^{th} percentiles. Values are displayed after winsorizing the variables at the 1^{st} and 99^{th} percentiles. See Appendix 1 for variable definition information.

TABLE 5 Sample sorts

Panel A: Variance risk premiums

	Dependent Variable = *VRP*			
	Sort Variable:			
	LEVEL1AT	*LEVEL2AT*	*LEVEL3AT*	*LEVEL23AT*
Q1 (Low)	-0.265 (11.92***)	-0.213 (10.68***)	-0.254 (11.57***)	-0.232 (12.63***)
Q2	-0.267 (13.88***)	-0.268 (13.59***)	-0.247 (13.21***)	-0.245 (11.81***)
Q3	-0.224 (10.84***)	-0.252 (12.08***)	-0.230 (10.27***)	-0.246 (11.69***)
Q4 (High)	-0.229 (11.21***)	-0.244 (12.34***)	-0.261 (11.62***)	-0.271 (12.67***)
Q4 - Q1	0.036	-0.031	-0.007	-0.039
F-test (*Q4 - Q1*)	3.436*	3.449*	0.095	4.569**
Adj. R^2	0.2%	0.2%	0.0%	0.1%

Panel B: Straddle returns

	Dependent Variable = *STRADDLE_RET*			
	Sort Variable:			
	LEVEL1AT	*LEVEL2AT*	*LEVEL3AT*	*LEVEL23AT*
Q1 (Low)	-0.210 (8.50***)	-0.169 (7.43***)	-0.210 (7.61***)	-0.194 (9.36***)
Q2	-0.235 (11.91***)	-0.228 (11.05***)	-0.219 (10.82***)	-0.213 (9.38***)
Q3	-0.210 (8.12***)	-0.228 (9.59***)	-0.206 (7.81***)	-0.217 (9.09***)
Q4 (High)	-0.198 (8.97***)	-0.222 (10.27***)	-0.224 (9.74***)	-0.238 (11.25***)
Q4 - Q1	0.012	-0.053	-0.014	-0.044
F-test (*Q4 - Q1*)	0.461	11.337***	0.413	7.450***
Adj. R^2	0.0%	0.1%	0.0%	0.0%

Note: This table displays the regression results using binary variables to represent the month-industry quartiles (*Q1*, *Q2*, *Q3*, and *Q4*) after sorting the data set using the indicated sorting variable. *N* = 56,099 for all regressions. Panel A uses *VRP* as the dependent variable and Panel B uses *STRADDLE_RET* as the dependent variable. The first value is the estimated coefficient and second value in parentheses is the associated *t*-statistic. Variables are winsorized at the 1st and 99th percentiles. See Appendix 1 for variable definition information. Industries are defined by three-digit SIC codes. The *F*-test is a two-sided test if the estimate coefficient for *Q4* is statistically different from the estimated coefficient for *Q1*. ***, **, and * denote coefficients or tests significant at 0.01, 0.05, and 0.10 levels respectively using two-sided tests. All standard errors are clustered at the month and firm level.

TABLE 6 Regression results – variance risk premiums

	Dependent Variable = *VRP*					
	(1)	(2)	(3)	(4)	(5)	(6)
LEVEL1AT	0.019 (3.40***)	0.004 (0.91)	0.005 (1.02)	0.005 (1.10)	0.001 (0.10)	0.001 (0.20)
LEVEL2AT	0.006 (0.99)	0.004 (0.53)	0.002 (0.27)	0.005 (0.78)	-0.019 (2.45**)	-0.008 (2.22**)
LEVEL3AT	-0.045 (4.99***)	-0.044 (4.68***)	-0.045 (4.49***)	-0.029 (3.28***)	-0.034 (4.73***)	-0.015 (3.91***)
LEVEL1LT			-0.004 (0.75)	-0.006 (1.36)	-0.002 (0.50)	0.000 (0.17)
LEVEL2LT			0.008 (1.41)	-0.008 (1.62)	0.005 (1.05)	0.001 (0.66)
LEVEL3LT			0.002 (0.35)	0.005 (0.88)	0.005 (0.95)	0.003 (1.14)
LN_MRKCAP				0.084 (10.88***)	-0.018 (2.13**)	-0.004 (0.81)
LEV				0.002 (0.28)	-0.012 (1.16)	-0.004 (1.02)
ROA				0.017 (3.75***)	0.023 (3.57***)	0.010 (3.29***)
LOSS				0.000 (0.00)	0.104 (7.96***)	0.031 (4.74***)
LN_IMPVOL					-0.307 (29.62***)	-0.114 (17.14***)
IMPSKEW					0.013 (4.41***)	0.005 (2.60**)
IMPCURVE					-0.033 (4.32***)	-0.010 (2.84***)
LN_SPREAD						-0.248 (49.27***)
Adj. R^2	16.4%	21.0%	21.0%	24.1%	48.6%	62.6%
Fixed Effects	Month	Month x Industry	Month x Industry	Month x Industry	Month x Industry	Month x Industry

Note: This table displays the regression results using *VRP* as the dependent variable. *N* = 56,099 for all regressions. Continuous variables are winsorized at the 1st and 99th percentiles and continuous independent variables are scaled to have unit variance, zero means. See Appendix 1 for variable definition information. The first value is the estimated coefficient and second value in parentheses is the associated *t*-statistic. Industries are defined by three-digit SIC codes. ***, **, and * denote coefficients significant at 0.01, 0.05, and 0.10 levels respectively using two-sided tests. All standard errors are clustered at the month and firm level.

TABLE 7 Regression results – straddle returns

	Dependent Variable = *STRADDLE_RET*					
	(1)	(2)	(3)	(4)	(5)	(6)
LEVEL1AT	0.023 (4.47***)	0.007 (1.33)	0.006 (1.27)	0.005 (1.02)	0.003 (0.51)	0.003 (0.75)
LEVEL2AT	-0.004 (0.54)	-0.006 (0.75)	-0.008 (1.09)	-0.005 (0.73)	-0.016 (2.07**)	-0.010 (1.57)
LEVEL3AT	-0.030 (4.33***)	-0.030 (4.24***)	-0.033 (4.30***)	-0.021 (2.99***)	-0.024 (3.65***)	-0.014 (2.48**)
LEVEL1LT			0.000 (0.00)	-0.002 (0.30)	0.001 (0.13)	0.002 (0.42)
LEVEL2LT			0.007 (1.26)	-0.003 (0.55)	0.002 (0.46)	0.000 (0.04)
LEVEL3LT			0.006 (1.13)	0.008 (1.49)	0.008 (1.52)	0.007 (1.72*)
LN_MRKCAP				0.059 (6.58***)	0.017 (1.74*)	0.024 (2.77***)
LEV				0.002 (0.32)	-0.004 (0.48)	0.000 (0.01)
ROA				0.026 (4.58***)	0.028 (4.41***)	0.021 (3.76***)
LOSS				0.056 (3.50***)	0.094 (6.00***)	0.054 (4.08***)
LN_IMPVOL					-0.135 (14.48***)	-0.031 (3.12***)
IMPSKEW					-0.021 (6.96***)	-0.026 (8.67***)
IMPCURVE					-0.028 (3.66***)	-0.015 (2.47**)
LN_SPREAD						-0.133 (19.92***)
Adj. R^2	8.8%	16.0%	16.1%	16.8%	18.6%	20.4%
Fixed Effects	Month	Month x Industry	Month x Industry	Month x Industry	Month x Industry	Month x Industry

Note: This table displays the regression results using *STRADDLE_RET* as the dependent variable. *N* = 56,099 for all regressions. Continuous variables are winsorized at the 1st and 99th percentiles and continuous independent variables are scaled to have unit variance, zero means. See Appendix 1 for variable definition information. The first value is the estimated coefficient and second value in parentheses is the associated *t*-statistic. Industries are defined by three-digit SIC codes. ***, **, and * denote coefficients significant at 0.01, 0.05, and 0.10 levels respectively using two-sided tests. All standard errors are clustered at the month and firm level.

TABLE 8 Sample splits by firm size

	Dependent Variable = *VRP*			
	Small Firms		Large Firms	
	(1)	(2)	(3)	(4)
LEVEL1AT	0.001 (0.09)	0.002 (0.52)	0.004 (0.37)	0.000 (0.01)
LEVEL2AT	-0.009 (0.65)	-0.004 (0.72)	-0.028 (2.85***)	-0.012 (2.85***)
LEVEL3AT	-0.054 (5.06***)	-0.022 (4.14***)	-0.009 (1.16)	-0.008 (1.76*)
LEVEL1LT	-0.003 (0.56)	0.000 (0.11)	-0.006 (0.76)	-0.002 (0.59)
LEVEL2LT	-0.002 (0.56)	-0.001 (0.45)	0.004 (0.50)	0.002 (0.78)
LEVEL3LT	-0.003 (0.37)	-0.001 (0.22)	0.009 (1.28)	0.005 (1.74*)
LN_MRKCAP	-0.023 (2.05**)	-0.003 (0.67)	-0.014 (1.38)	-0.005 (1.16)
LEV	-0.025 (1.85*)	-0.008 (1.41)	0.004 (0.31)	0.001 (0.25)
ROA	0.022 (2.85***)	0.009 (2.55**)	0.001 (0.13)	0.001 (0.31)
LOSS	0.060 (3.52***)	0.012 (1.44)	0.108 (6.48***)	0.035 (4.08***)
LN_IMPVOL	-0.328 (29.35***)	-0.121 (15.48***)	-0.281 (19.73***)	-0.109 (13.15***)
IMPSKEW	0.016 (4.11***)	0.007 (2.62***)	0.004 (1.16)	0.002 (0.84)
IMPCURVE	-0.043 (3.94***)	-0.011 (2.27**)	-0.017 (1.90*)	-0.007 (2.01**)
LN_SPREAD		-0.262 (40.47***)		-0.218 (37.24***)
Adj. R^2	48.6%	61.4%	52.7%	65.9%
N	28,667	28,667	27,432	27,432
Fixed Effects	Month x Industry	Month x Industry	Month x Industry	Month x Industry

Note: This table displays the regression results using *VRP* as the dependent variable when splitting the sample on firm size. Small (large) firms are firms with book assets equal to or less than (larger than) the associated median month-industry value. Continuous variables are winsorized at the 1st and 99th percentiles and continuous independent variables are scaled to have unit variance, zero means. See Appendix 1 for variable definition information. The first value is the estimated coefficient and second value in parentheses is the associated *t*-statistic. Industries are defined by three-digit SIC codes. ***, **, and * denote coefficients significant at 0.01, 0.05, and 0.10 levels respectively using two-sided tests. All standard errors are clustered at the month and firm level.

TABLE 9 Sample splits by year

	Dependent Variable = *VRP*					
	2009 - 2011		2012 - 2014		2015 - 2017	
	(1)	(2)	(3)	(4)	(5)	(6)
LEVEL1AT	0.003 (0.31)	0.001 (0.30)	0.010 (0.93)	0.005 (1.09)	-0.010 (1.14)	-0.003 (0.87)
LEVEL2AT	-0.018 (1.95*)	-0.011 (2.30**)	-0.001 (0.08)	0.001 (0.26)	-0.035 (4.05***)	-0.013 (2.42**)
LEVEL3AT	0.000 (0.02)	-0.002 (0.57)	-0.028 (3.09***)	-0.011 (2.25**)	-0.062 (5.76***)	-0.027 (3.60***)
LEVEL1LT	-0.003 (0.48)	0.000 (0.05)	-0.004 (0.71)	-0.003 (1.49)	-0.001 (0.26)	0.002 (0.72)
LEVEL2LT	0.008 (1.53)	0.004 (1.36)	0.002 (0.39)	0.001 (0.60)	0.013 (1.90*)	0.001 (0.35)
LEVEL3LT	0.000 (0.04)	0.000 (0.08)	0.002 (0.25)	0.000 (0.04)	0.019 (1.88*)	0.009 (2.05**)
LN_MRKCAP	0.009 (0.92)	0.004 (0.60)	-0.027 (2.41**)	-0.005 (0.78)	-0.033 (2.71**)	-0.008 (1.00)
LEV	0.009 (0.78)	0.000 (0.09)	-0.027 (1.97*)	-0.008 (1.52)	-0.022 (1.77*)	-0.005 (0.96)
ROA	0.000 (0.01)	0.001 (0.12)	0.034 (4.68***)	0.016 (4.19***)	0.035 (4.64***)	0.013 (3.40***)
LOSS	0.080 (6.13***)	0.032 (3.24***)	0.080 (4.21***)	0.020 (2.25**)	0.102 (4.82***)	0.030 (2.52**)
LN_IMPVOL	-0.197 (10.91***)	-0.095 (8.47***)	-0.325 (26.70***)	-0.113 (11.68***)	-0.302 (27.48***)	-0.111 (11.14***)
IMPSKEW	0.019 (4.14***)	0.009 (2.97***)	0.010 (1.92*)	0.003 (0.77)	0.014 (3.51***)	0.006 (2.00*)
IMPCURVE	-0.034 (3.68***)	-0.019 (3.54***)	-0.051 (4.95***)	-0.011 (2.15**)	-0.010 (1.04)	-0.002 (0.33)
LN_SPREAD		-0.190 (24.44***)		-0.264 (35.38***)		-0.250 (28.06***)
Adj. R^2	50.8%	62.3%	48.4%	63.1%	48.8%	62.0%
N	15,104	15,104	18,782	18,782	22,213	22,213
Fixed Effects	Month x Industry	Month x Industry	Month x Industry	Month x Industry	Month x Industry	Month x Industry

Note: This table displays the regression results using *VRP* as the dependent variable when splitting the sample on observation years. Continuous variables are winsorized at the 1st and 99th percentiles and continuous independent variables are scaled to have unit variance, zero means. See Appendix 1 for variable definition information. The first value is the estimated coefficient and second value in parentheses is the associated *t*-statistic. Industries are defined by three-digit SIC codes. ***, **, and * denote coefficients significant at 0.01, 0.05, and 0.10 levels respectively using two-sided tests. All standard errors are clustered at the month and firm level.

TABLE 10 Robustness tests – ranks

	Dependent Variable:			
	VRP		*STRADDLE_RET*	
	(1)	(2)	(3)	(4)
LEVEL1AT	-0.001 (0.03)	0.001 (0.11)	0.010 (0.95)	0.011 (1.32)
LEVEL2AT	-0.030 (1.50)	-0.020 (1.75*)	-0.036 (2.54**)	-0.031 (2.82***)
LEVEL3AT	-0.041 (2.69***)	-0.026 (2.67***)	-0.034 (2.99***)	-0.028 (2.84***)
LEVEL1LT	0.022 (1.19)	0.008 (0.78)	0.015 (1.11)	0.009 (0.85)
LEVEL2LT	-0.014 (1.15)	-0.003 (0.51)	-0.009 (0.99)	-0.005 (0.66)
LEVEL3LT	0.009 (0.62)	0.000 (0.03)	0.014 (1.34)	0.011 (1.23)
LN_MRKCAP	-0.015 (0.81)	-0.009 (0.75)	0.041 (3.01***)	0.043 (3.55***)
LEV	0.019 (0.95)	0.009 (0.84)	0.014 (1.05)	0.010 (0.96)
ROA	0.052 (3.39***)	0.030 (3.16***)	0.042 (3.71***)	0.033 (3.42***)
LOSS	0.062 (7.16***)	0.030 (5.16***)	0.052 (7.18***)	0.039 (6.00***)
LN_IMPVOL	-0.522 (23.56***)	-0.285 (16.54***)	-0.172 (13.11***)	-0.080 (5.79***)
IMPSKEW	0.030 (4.57***)	0.018 (4.01***)	-0.020 (3.84***)	-0.024 (5.02***)
IMPCURVE	-0.012 (0.74)	-0.005 (0.55)	-0.015 (1.26)	-0.012 (1.22)
LN_SPREAD		-0.433 (36.81***)		-0.167 (17.14***)
Adj. R^2	42.0%	52.3%	15.6%	17.2%
N	56,099	56,099	56,099	56,099
Fixed Effects	Month x Industry	Month x Industry	Month x Industry	Month x Industry

Note: This table displays the regression results when converting variable to ranks. All continuous variables are converted to percentile ranks. See Appendix 1 for variable definition information. The first value is the estimated coefficient and second value in parentheses is the associated *t*-statistic. Industries are defined by three-digit SIC codes. ***, **, and * denote coefficients significant at 0.01, 0.05, and 0.10 levels respectively using two-sided tests. All standard errors are clustered at the month and firm level.

TABLE 11 Implied volatility forecast precision

	Dependent Variable: *ABS_VRP*					
	(1)	(2)	(3)	(4)	(5)	(6)
LEVEL1AT	-0.005 (1.34)	-0.002 (0.35)	-0.002 (0.67)	-0.002 (1.26)	-0.002 (0.76)	-0.002 (0.90)
LEVEL2AT	-0.002 (0.41)	0.016 (2.59**)	0.007 (2.46**)	0.001 (0.47)	0.005 (2.22**)	0.003 (1.85*)
LEVEL3AT	0.028 (3.98***)	0.032 (5.47***)	0.018 (5.40***)	0.011 (4.51***)	0.014 (5.50***)	0.011 (5.21***)
VRP				-0.272 (28.04***)	-0.246 (27.16***)	-0.214 (22.05***)
LEVEL1LT	0.002 (0.55)	-0.001 (0.27)	-0.003 (1.36)	-0.002 (1.50)	-0.002 (1.58)	-0.003 (2.22**)
LEVEL2LT	0.006 (1.58)	-0.003 (0.95)	-0.001 (0.35)	0.001 (0.86)	-0.001 (0.46)	0.000 (0.00)
LEVEL3LT	-0.004 (0.98)	-0.005 (1.04)	-0.003 (1.18)	-0.001 (0.87)	-0.002 (0.96)	-0.001 (0.92)
LN_MRKCAP	-0.072 (12.22***)	0.002 (0.31)	-0.008 (2.17**)	-0.021 (6.26***)	-0.008 (2.18**)	-0.010 (3.09***)
LEV	-0.002 (0.27)	0.009 (1.14)	0.003 (0.88)	0.000 (0.14)	0.002 (0.85)	0.001 (0.50)
ROA	-0.012 (3.10***)	-0.016 (3.34***)	-0.006 (2.77***)	-0.001 (0.61)	-0.003 (1.68*)	-0.001 (0.89)
LOSS	0.008 (0.79)	-0.067 (6.50***)	-0.013 (2.20**)	0.008 (1.45)	-0.010 (1.93*)	0.001 (0.30)
LN_IMPVOL		0.225 (19.47***)	0.082 (12.17***)		0.056 (10.50***)	0.028 (5.91***)
IMPSKEW		-0.008 (3.21***)	-0.002 (1.17)		-0.001 (0.65)	0.000 (0.01)
IMPCURVE		0.026 (4.25***)	0.009 (2.78***)		0.008 (3.12***)	0.004 (1.94*)
LN_SPREAD			0.183 (29.89***)			0.065 (18.23***)
Adj. R^2	14.5%	36.1%	48.9%	61.1%	62.0%	63.2%
Fixed Effects	Month x Industry	Month x Industry	Month x Industry	Month x Industry	Month x Industry	Month x Industry

Note: This table displays the regression results using *ABS_VRP* as the dependent variable. N = 56,099 for all regressions. Continuous variables are winsorized at the 1st and 99th percentiles and continuous independent variables are scaled to have unit variance, zero means. See Appendix 1 for variable definition information. The first value is the estimated coefficient and second value in parentheses is the associated t-statistic. Industries are defined by three-digit SIC codes. ***, **, and * denote coefficients significant at 0.01, 0.05, and 0.10 levels respectively using two-sided tests. All standard errors are clustered at the month and firm level.