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Ambiguity in Option Markets – Evidence from SEOs

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Abstract

Seasoned equity offerings (SEOs) typically provide investors with information, or signals, that are stock price relevant. This information, however, is generally intangible, meaning market participants have incomplete knowledge about its quality. Investors thus tend to regard it as ambiguous. To calculate a related ambiguity premium, we use straddle returns to explore the difference between option-implied and realised volatility following SEO events. After controlling for common risk factors, we find significantly positive alphas that can proxy for the ambiguity premium. In line with previous research, we find that the estimated ambiguity premium is positively correlated with firms' fundamental data intangibility, as proxied for by the skewness of stock returns.

Keywords: Ambiguity; Option-Implied Information; Information Tangibility; Seasoned Equity Offerings (SEOs); Straddle; Volatility Trading Strategy.
JEL Codes: C21; G14; G32.

1 Introduction

Seasoned equity offerings (SEOs) are an important source of external financing for publicly listed companies. They are frequently accompanied by negative stock returns, but investors' reactions to them can also vary considerably (Kim and Purnanandam, 2006).

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Investors in this situation must process information (or a signal) about the determinants and economic consequences of the SEO that is expected to be informative about, for example, future financing costs, dividends, capital investments, refinancing, liquidity squeezes, corporate control, stock market microstructure, and stock price valuations. This information thus impacts the stock price (see, e.g., Loughran and Ritter, 1995, 1997; Graham and Harvey, 2001; Baker and Wurgler, 2002; Shleifer and Vishny, 2003; Khan, Kogan and Serafeim, 2012).

The information, however, is *intangible*, meaning that market participants have incomplete knowledge about the signals' quality (see, e.g., Autore, Bray and Peterson, 2009, who point out the «fuzziness» of the intended use of SEO proceeds). When information (signal) quality is difficult to assess or judge, market participants regard it as *ambiguous*. Epstein and Schneider (2008) argue that, under those circumstances, market participants will not update their beliefs as they do in Bayesian models, but rather act as if they have multiple priors (beliefs) – or a range – in mind when deciding how to treat *ambiguous* information. In this setting, Epstein and Schneider (2003) use recursive multiple-priors utility, and show how ambiguity-averse market participants will act as if they can maximise their expected utility under a worst-case belief from a range of priors.

Thus, option-writers on SEO firms are confronted with *intangible* information about the SEO, and form their beliefs from a *family of likelihoods* for the resulting volatility, $\sigma_{SEO} \in [\underline{\sigma}_{SEO}, \overline{\sigma}_{SEO}]$. In Epstein and Schneider's (2003) model, ambiguity-averse option-writers base their volatility decisions on the worst-case scenario, which would actually hurt them the most ($\overline{\sigma}_{SEO}$). Therefore, the choice of ($\overline{\sigma}_{SEO}$) by option-writers can be interpreted as an ambiguity premium, which is required as compensation for the ambiguous (*intangible*) information.

However, note that the ambiguity premium should not have the same expected mean, even if the SEO announcement of two firms is equal (same signal quality). This is because market participants require higher compensation (a higher ambiguity premium) for low signal quality when a firm's fundamental data is more volatile (*intangible*). If the fundamental data is more constant and predictable, market participants will not be concerned (or will be less so) about signal quality. The demanded ambiguity premium in that case will be small or actually zero, even if the signal is ambiguous.

In contrast, given low signal quality, market participants will demand increasing ambiguity premiums for firms with more volatile or *intangible* fundamental data. Epstein and Schneider (2008) argue that the skewness of the return distribution «measures the relative importance of tangible and intangible information in a market: Negative skewness should be observed for assets about which there is relatively more intangible information» (p. 199). The skewness is thus expected to be lower for firms with relatively more intangible information, which can make a judgment about the SEO event more difficult. This relationship implies a negative correlation between the ambiguity premium and skewness[1].

[1] In a similar context, it was found that firm opacity (transparency level of financial statements) as measured by e.g. earnings management is associated with its stock returns distribution. More specifically, an increase in firm opacity translates into both less disclosure of «firm specific information» and higher «crash risk» (see Hutton *et al.*, 2009). Given this overlap, it is not surprising that skewness of stocks' return distribution, as our measure of intangibility,

In an efficient market, one would expect the option-implied volatility to be a good predictor of future realised volatility (implying an ambiguity premium of zero). If investors formulate their expectations rationally, any changes in implied volatility should fully incorporate the set of new information accumulated to date. However, we find a strong divergence between option-implied and realised volatility following equity issuance: Realised volatility exhibits a strong decrease after issuance, while the expected volatility implied from option markets remains constant, thus overestimating realised volatility. We argue that this «overestimation» in realised volatility is a reflection of the ambiguity premium demanded by option-writers as compensation for the ambiguous (*intangible*) information.

To measure the magnitude of this possible ambiguity premium and to test for its economic significance, we analyse the risk-adjusted returns of short straddles (a volatility trading strategy) following issuance (see, e.g., Goyal and Saretto, 2009; Coval and Shumway, 2001; and Arisoy, Salih and Akdeniz, 2007, who use straddle portfolios to analyse volatility dynamics). We find that using straddle portfolios to examine the differences between option-implied and realised volatility can lead on average to statistically significant risk-adjusted positive returns of around 5.5% per month for the one-month period after SEO issuance. However, when grouping the SEO events into quartiles of stocks with lowest to highest skewness, we find risk-adjusted alphas (as proxies for the ambiguity premium) that are about 30% higher for the quartile in which stocks with the lowest skewness are grouped. We also find that the risk-adjusted alphas decline monotonically with an increase in skewness, and that the ambiguity premium is statistically not different from zero for the quartile with comparably high skewness (companies with comparably tangible fundamental data). This result mirrors Epstein and Schneider's (2008) theoretical argument that the ambiguity premium is low or even zero for companies with predominantly tangible information, even if the SEO announcement itself is intangible.

This paper thus contributes to the extant literature in several ways. First, and most importantly, we not only document a market inefficiency, we also embed our findings in Epstein and Schneider's (2008) theory-based framework. We are therefore able to explain how ambiguity-averse investors process ambiguous signals (SEO events) in option markets that significantly impact stock price development, depending on a firm's fundamental data volatility or information tangibility. We also document that the ambiguity premium is positively correlated with firms' fundamental data intangibility, as proxied for by the skewness of stock returns.

Second, we relate our research to a recent strand of literature that examines market efficiency through option-implied information. Our work differs in that we concentrate on stock market options for one specific corporate event. Most previous studies on option market misreactions have estimated the degree of overreaction for a general market index only. Furthermore, in contrast to the large volume of work on stock market misreactions around equity offerings, our paper uses option-implied information to analyse investor behaviour around corporate events. The benefits of examining options rather than stocks

has a positive correlation with firm opacity. However, in our context we are not explaining risk premia in a cross-sectional context and instead we aim to identify risk premia in the event of an SEO. For this event, investors are mostly interested in how the proceeds will be used and not in reevaluating a crash risk. Therefore, we believe that skewness is a cleaner measure for information intangibility than firm opacity.

have been shown in Stein (1989). In option valuation, the only unknown variable is the volatility of the underlying asset, while equity and bond prices are affected by additional factors, such as changes in common risk premiums.

Third, we relate our paper to a new strand of literature that examines volatility trading strategies for the analysis of risk dynamics. Goyal and Saretto (2009), Coval and Shumway (2001), and Arisoy, Salih and Akdeniz (2007) are among those who have used straddle strategies to analyse volatility dynamics. Straddle portfolios neutralise the impact of movements in the underlying stocks, and can be useful in analysing risk dynamics.

To the best of our knowledge, however, ours is the first paper to analyse risk dynamics around SEOs using straddle returns. Most prior research has focused on stock market beta dynamics as a means to analyse risk around corporate events. Our paper contributes to the current debate on risk dynamics by identifying an innovative trading strategy that links information (processing) from option and stock markets to abnormal returns, and provides at least a partial explanation that is theoretically well-grounded.

The remainder of the paper is organised as follows. Section 2 describes our data sources, filter criteria, and matching procedures. Section 3 then presents our main results on the cross-sectional analysis of risk dynamics in stock and option markets over time. Section 4 examines straddle strategies based on the difference between option-implied and realised volatility. It also discusses possible alternative explanations in a robustness check. Section 5 concludes.

2 Data

We conduct an empirical analysis using daily stock and option data for our sample period of January 1996-December 2005. The data come from several sources: The option data originate from OptionMetrics, the stock data come from the Center for Research in Security Prices (CRSP), firm characteristics and balance sheet information is obtained from Standard & Poor's (S&P) Compustat database, and the SEO data come from the Securities Data Company's (SDC) Global New Issues Database. The option data cover all exchange-listed call and put options on U.S. equities, with approximately 7 million options per month.

OptionMetrics also reports implied volatility for each option. The implied volatilities on individual stock options, which are American, are calculated using a Cox-Ross-Rubinstein (1979) binomial tree model, taking into account discrete dividend payments and the potential for early exercise. The CRSP database includes monthly and daily price quotes for stocks on the New York Stock Exchange (NYSE), the American stock exchange (the AMEX), and the Nasdaq. The SDC database contains traditional SEOs from the 1996-2005 time period.

Our first step is to filter the SEO data following Carlson, Fisher and Giammarino (2010). We exclude utilities and financials, and keep only common stock issues traded on the NYSE, the AMEX, or the Nasdaq by U.S. companies that are not coded as IPOs, unit issues, ADRs, or ADSs. If a firm had more than one SEO, we treat the transactions as separate observations. Furthermore, we require the SEO securities to have valid stock price data in CRSP. We obtain a total of 4,232 SEO events that fulfil these criteria[2].

Our next step is to match the 4,232 SEO events with the standardised option dataset in OptionMetrics. For each firm and trading day, we take standardised equity-implied volatilities and premiums for ATM (at-the-money) call and put options, with a one-month time to maturity. In OptionMetrics, the implied volatilities of standardised ATM options are calculated by interpolating the volatility surface. The forward price of the underlying security is calculated first, using the zero curve and the projected distributions. The volatility surface points are then linearly interpolated to the forward price and the target expiration in order to generate ATM-implied volatilities. A standardised option is included only if enough option price data exist on that date to accurately interpolate the required values.

Berndt and Ostrovnaya (2014), Rogers, Skinner and Buskirk (2009), Stein and Stone (2013), and Ordu and Schweizer (2015, 2017) have all used OptionMetrics standardised option data for their analyses. Standardised options are generally believed to have two advantages over traded options. First, the data granularity is higher, because standardised options are constructed to be ATM. We obtain 1,753 observations with standardised option data, and only 290 observations with traded option data.

Second, standardised option data are more suitable for the accurate calculation of monthly straddle portfolio returns. As we note later, this return calculation is necessary in order to analyse volatility trading strategies. Moreover, because standardised option duration is held constant, the straddle returns are not affected by changes in option prices due to, e.g., variations in time to maturity.

Figure 1 illustrates the «maturity mismatch problem» of traded options, which is also described in Rogers, Skinner and Buskirk (2009) and Patell and Wolfson (1979, 1981). Traded options normally mature only on the third Friday of the month. However, obviously, not all SEO events take place on the same day, so options available on the straddle forming dates (the days following the SEO event) have expiration dates that can differ by up to one month. This implies that, when we close a straddle position after one calendar month, we would not expect the underlying options to expire on this date.

To avoid obtaining returns that are not perfectly comparable due to the *maturity mismatch problem*, we use standardised option data. However, using traded options that do not expire at the straddle closing day can lead to inappropriate and biased results. This is because the price of an option on the closing date reflects not only the development of the underlying asset up to that date, but also future market expectations up to the expiration date. Therefore, only options that expire at the closing date are ideal measures of past underlying performance or risk dynamics[3]. Table 1 provides summary statistics for the matched sample.

Table 1 shows that the number of SEOs fluctuates from year to year. Most of the offerings we consider here took place around the year 2000. That year also saw the highest amount of gross proceeds and the largest market capitalisation.

[2] We use «SEO event» or «event date» throughout this paper to refer to the issue date of the seasoned equity offering as reported in SDC.

[3] As a robustness check, we replicate our results in section 5 with the traded option data sample. Our results remain qualitatively highly similar.

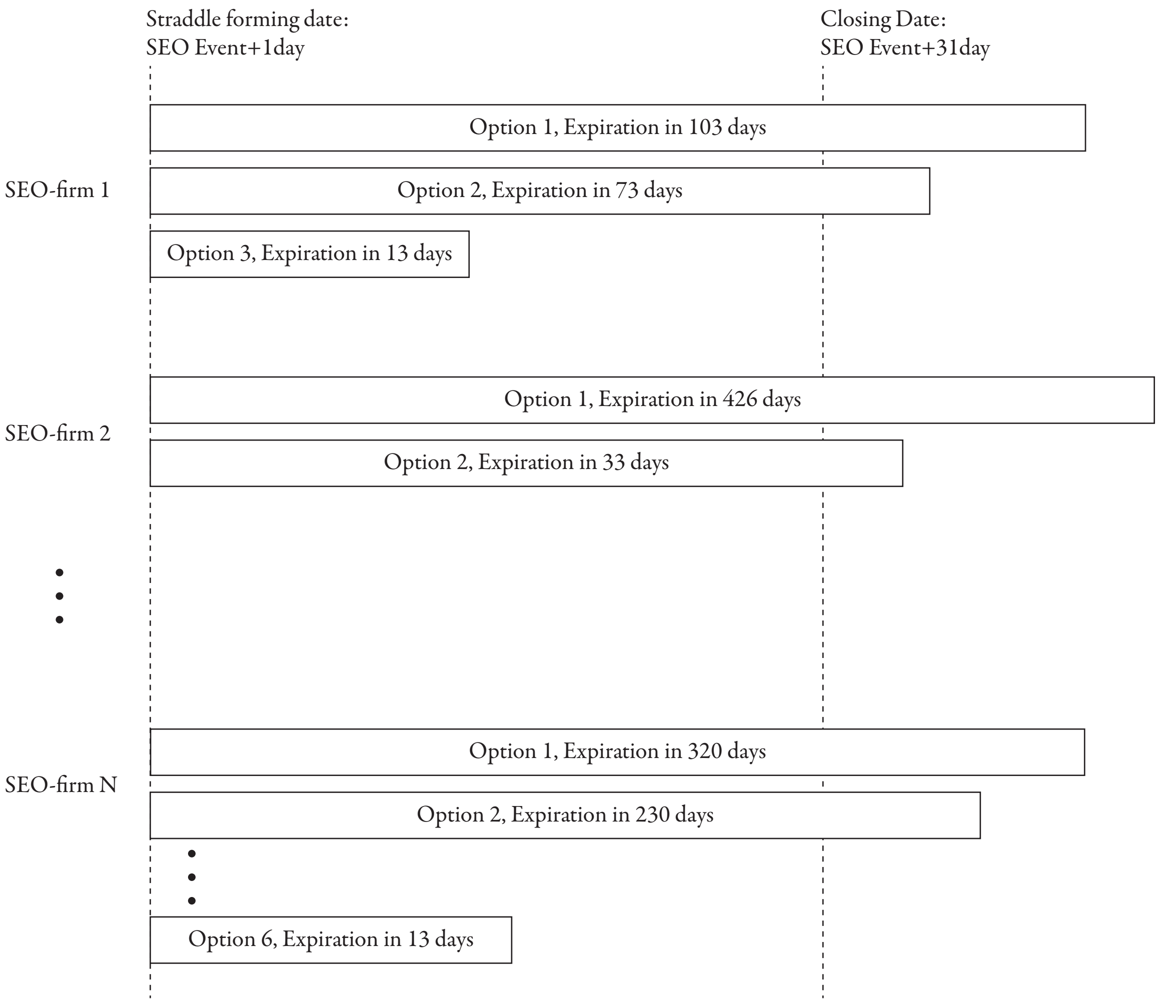

Figure 1: Option closing before expiration date.

This figure illustrates the task of calculating monthly option returns for SEO securities on the day following the SEO event (the straddle formation date). Firms that undergo an SEO (SEO firm) have several options available to them on the date of issuance. Because options generally mature only on the third Friday of the month, the options on the straddle formation date usually have expiration dates different than one month.

Table 1: SEO distributions by year

Year	Aggregate gross proceeds (Mil. USD)	Market Cap (Mil. USD)	No. of offerings
1996	166	1,275	154
1997	177	1,631	161
1998	269	4,139	147
1999	302	4,004	218
2000	363	6,396	205
2001	232	2,494	183
2002	168	1,611	170
2003	141	1,626	174
2004	194	3,225	189
2005	209	2,782	152
Total	226	3,022	1,753

The sample consists of common stock issues traded on the NYSE, AMEX, or Nasdaq that are not coded as IPOs, unit issues, ADRs, or ADSs. Regulated utilities (SIC = 481 and 491-494) and financial institutions (SIC = 600-699) are excluded. To be included, firms must have valid quotes as of the date of issuance in the OptionMetrics standardised option database. Options are constructed to be ATM, and have exactly one month to maturity.

3 Volatility Dynamics

Next, we aim to contrast the realised volatility for stocks around SEO events with the option-implied volatility. Carlson, Fisher and Giammarino (2010) showed that realised volatility can exhibit substantial decreases on average, followed by increases around the SEO event. We want to determine how precisely option markets can predict these strong volatility fluctuations in stock markets. We thus compare realised volatility calculated from stock market returns with volatility implied from option prices. Implied volatility from option markets as a measure of capital market predictions of future risk provides a rich source of information about investor expectations of future stock volatility.

For each SEO stock, we calculate annualised monthly realised and implied volatility from the six-month period prior to the SEO event to the six-month period afterward[4]. We calculate monthly realised volatilities following the procedure in Schwert (1989). For each day, we calculate monthly historical variance by taking the sum of the squared daily returns (after subtracting the average daily return in the month) over the previous month's daily returns, as follows:

(1) $$\sigma^2_{HV} = \sum_{i=1}^{N_t} r^2_{it},$$

where there are N_t daily returns r_{it} in month t. We then annualise the resulting monthly realised volatilities[5].

We obtain monthly implied volatilities from the standardised option dataset[6]. We take the implied volatility of linearly interpolated ATM call and put options with thirty-day expiration dates[7]. In a similar analysis, Goyal and Saretto (2009) use ATM options with thirty-day expiration dates, and compare monthly implied volatility with monthly realised volatility.

For robustness and to better understand volatility dynamics, we also calculate realised and option-implied volatilities of matched firms as well as market aggregates. To find matched firms, we follow the «spirit» of Lyon, Barber and Tsai's (1999) matching procedure, but we *modify* it because the matched firm might not be an underlying firm for option contracts.

To elaborate, our *modified* Lyon, Barber and Tsai (1999) approach works as follows. First, we select all companies within the same two-digit SIC. We then calculate their rank-sums in terms of market value and book-to-market ratio. The lower the rank-sum,

[4] We show comparably short windows in Figure 2 around the SEO event (six months prior to six months afterward) because we focus here on short-term dynamics around the SEO, not long-term dynamics, as in Carlson, Fisher and Giammarino (2010).

[5] Calculating monthly realised volatility on a daily basis leads to strongly autocorrelated volatility data. However, because we aim to compare the dynamics of volatility between two markets, this problem is irrelevant.

[6] We choose the standardised option sample for our volatility dynamics analysis because options usually expire on the third Friday of the month. So a daily volatility comparison of traded options would be biased by a declining time to maturity. This problem can become especially severe as the option approaches its maturity date (see Rogers, Skinner and Buskirk, 2009, and Patell and Wolfson, 1979, 1981). In contrast, standardised options have exactly thirty days to maturity. See section 3 for other advantages of the standardised option dataset.

[7] Throughout this paper, we use «days» to refer to calendar days if not stated otherwise.

the «more similar» the firm will be to the SEO firm. We select the matched firm with the lowest rank-sum and option data available[8]. We then calculate the realised and implied volatility of the matched firms and of the market analogue to our SEO firm calculations.

Figure 2 shows the cross-sectional average of calculated volatilities around the SEO event for SEO firms, matches, and the market.

Because implied volatilities reflect annualised volatility expectations for the following month, implied volatility lags realised volatility by one month. This means that the implied volatility shown in Figure 2 on month x must be interpreted as the market prediction of future realised risk on month x + 1 (e.g., the following month).

Consistent with Carlson, Fisher and Giammarino's (2010) observations, realised volatility for SEO firms experiences strong fluctuations around equity issuance. As panel A of Figure 2 shows, realised volatility drops dramatically immediately after the SEO event (0M to 1M), and begins to increase strongly one month after issuance[9]. Carlson, Fisher and Giammarino (2010) refer to this pattern as a «volatility-timing» puzzle, and they attempt to offer some explanation for it as well as for the long-term development of realised volatility in a sixty-month window around the SEO event (see Figure 10, p. 4069, in Carlson, Fisher and Giammarino, 2010).

However, the authors do not provide any «rigorous» empirical evidence or formally test their explanations. We note that their paper concentrates more on analysing realised long-term risk dynamics, but they do not provide any theory or argumentation about the interaction of realised volatility and capital market predictions of future volatility (option-implied volatility) around the SEO event (short-term), which is at the core of our idea. Therefore, we also do not explain or contribute to solving the «volatility-timing» puzzle, but instead accept its validity.

Our focus here is different because we analyse the relationship between realised and option-implied volatility after the SEO event, and provide ambiguity-based arguments for why investors can earn statistically significant risk premiums. In comparison to the above described development of realised volatilities, the volatilities implied from option markets react differently. Realised volatility shows strong fluctuations around the SEO event, but implied volatility increases smoothly during the event. This suggests that option markets do not fully follow the risk dynamics around these events.

To be more precise, at the SEO date, realised volatility increases, while implied volatility – the market's expectations about future stock volatility for the following month – decreases. The direction (decrease) in future volatility is supported by the data and realised volatility decreases, but it is much stronger than expected at the SEO date (see Figure 2). The option market thus exhibits a higher volatility than the realised

[8] In unreported results, we match by firm size and industry classification only. The results were highly similar in magnitude and statistical significance, indicating they were not sensitive to the matching procedure. See, for example, Ritter (1991), Michaely, Thaler and Womack (1995), and Spiess and Affleck-Graves (1995) for the alternative matching procedures. Tables are available from the authors upon request.

[9] For a more detailed discussion of theoretical approaches to analysing patterns in financial returns around SEO events through real option theories, see Lucas and McDonald (1990) and Carlson, Fisher and Giammarino (2006, 2010). Note that the observed decrease in realised volatility is consistent with Hamada's (1972) financial leverage explanation. Hamada (1972) argues that the non-diversifiable risk should be greater for a firm with a higher debt-to-equity ratio than for a firm with a lower debt-to-equity ratio.

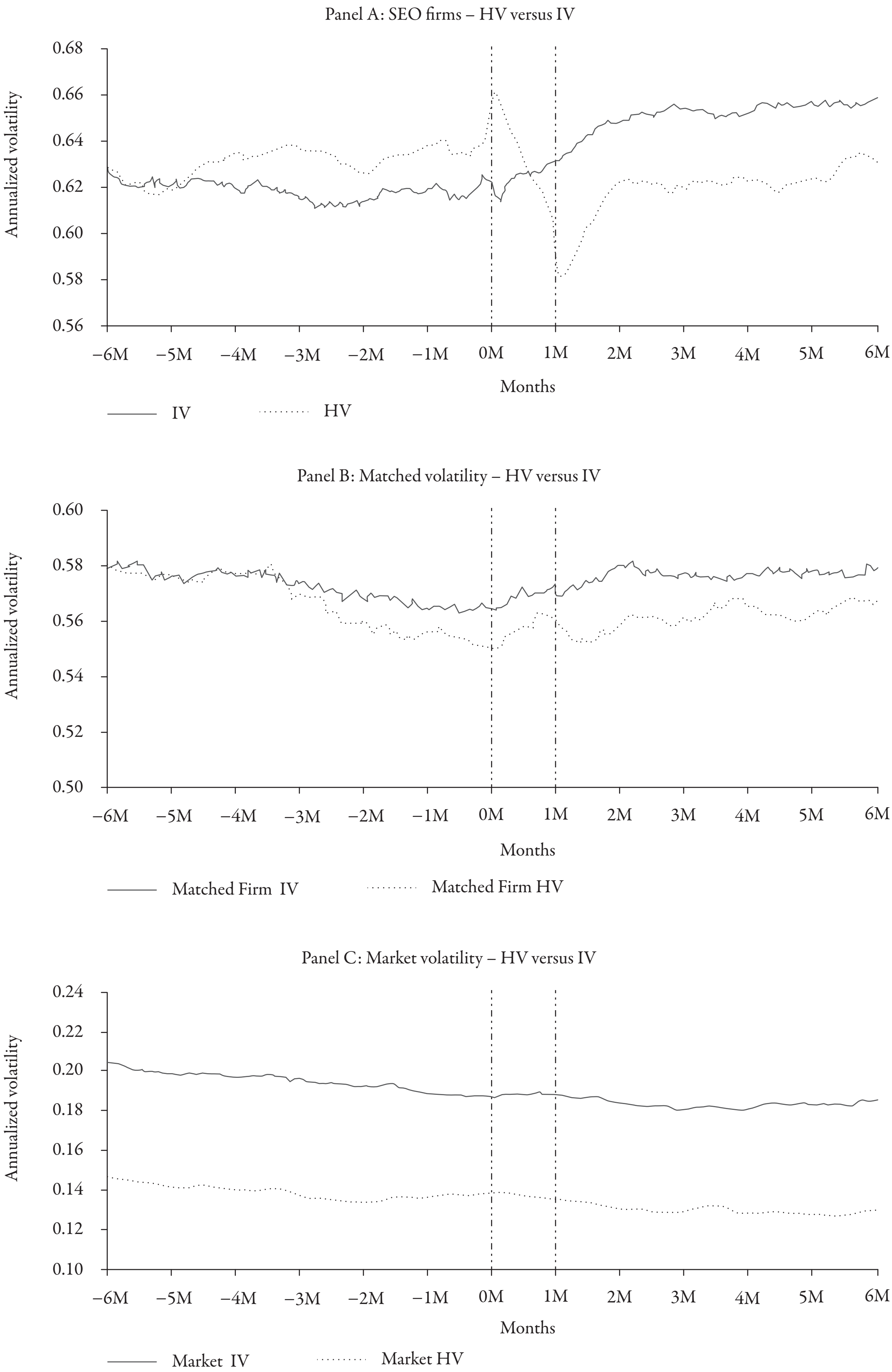

Figure 2: Comparison of realised and option-implied volatility around SEO events.

These figures compare realised (HV) and option-implied (IV) volatility dynamics from the six months prior to the SEO event to the five months afterward. Panel A displays volatility dynamics for SEO firms, panel B shows those for matched firms, and panel C shows those for the market. The solid lines show the average option-implied volatility, representing an annualised volatility expectation for the following calendar month. The dashed line shows realised volatility dynamics around SEO events. Realised and option-implied volatilities are both annualised. The dashed vertical grey lines are auxiliary lines marking the SEO event date and the one month date after the SEO event. All positive numbers on the x-axes are months after issuance; all negative numbers on the x-axes are months prior to issuance.

volatility one month after the event date. This overestimation may stem from the incapability of the option markets to correctly anticipate how stock market participants will react (misreactions). Or, it may be an ambiguity premium in the sense of Epstein and Schneider (2008), which is required as compensation for the ambiguous (*intangible*) information.

One month after the SEO event, we observe that the market prediction of volatility for the following month (two months after the SEO event) is almost the same or slightly higher than the final realised volatility. This could be a sign that option markets have processed the new information, that without the arrival of new *intangible* information an ambiguity premium is no longer required. Note also that, up to five months prior to the SEO event, implied volatility is slightly smaller than realised volatility; afterward, it reverses and remains at that level.

In panels B and C of Figure 2, we observe no decline for matched firms or market aggregates around issuance. This suggests that the sharp drop in volatility observed in panel A for SEO firms is not attributable to broad-based changes in volatility. Furthermore, we see that the average volatility of SEO firms and matched firms is much higher than the average volatility of market aggregates, which is consistent with observations made by Carlson, Fisher and Giammarino (2010).

Finally, panels A, B, and C of Figure 2 show that option-implied volatility is higher than realised volatility for matched firms and market aggregates (see also Poon and Granger, 2003, 2005). This observation is consistent with findings in Coval and Shumway (2001), who studied option returns on the S&P 500 with volatility trading strategies. Their results suggest that factors other than market risk, such as systematic risk, can lead to higher implied volatilities, and may be important for precisely pricing the risk in option markets. Thus, it is important to directly account for this kind of systematic risk in our empirical specifications.

4 Analysis of the Economic Significance of Using Straddle Strategies

This section provides a more complete analysis of the observations in Figure 2. In particular, we test whether volatility strategies that trade on the differences between realised and implied volatility following SEO events are profitable.

4.1 Methodology

Goyal and Saretto (2009) and Arisoy, Salih and Akdeniz (2007) are among those who have analysed risk dynamics with volatility trading strategies. We follow Goyal and Saretto (2009), and use straddle returns for our analysis of volatility dynamics. Straddle portfolios neutralise the impact of movements in underlying stocks, and are commonly used in analyses of volatility behaviour. Long/short straddles are formed by combining one long/short ATM call with one long/short ATM put option, with the same underlying, strike price, and maturity date.

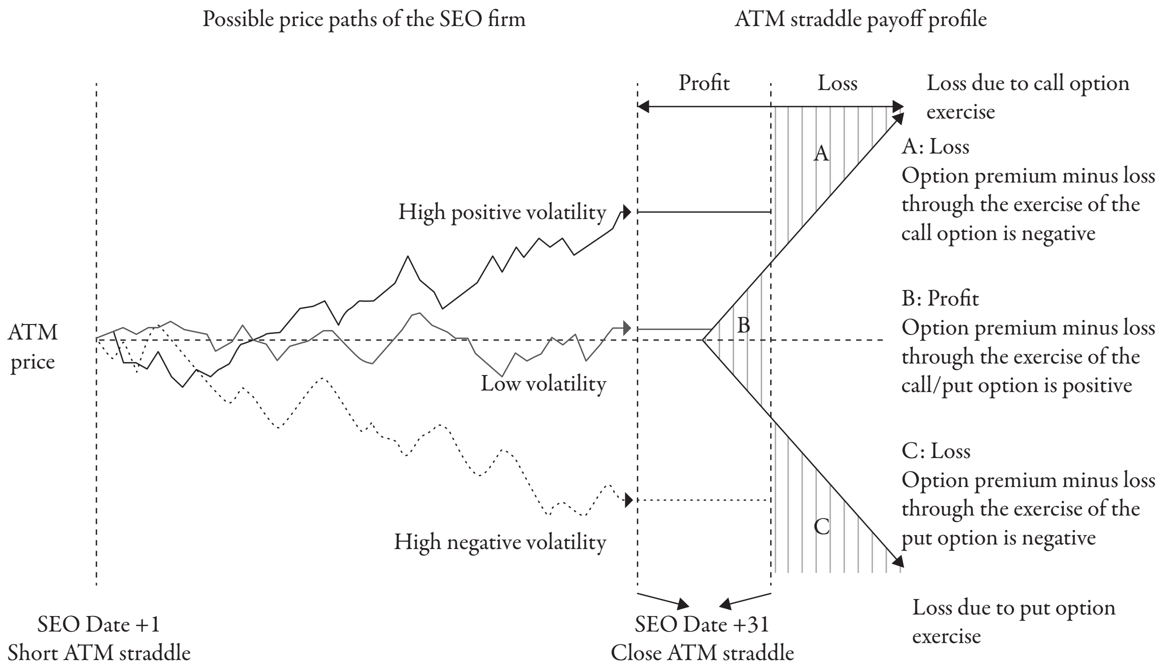

Figure 3: Payoff profile of a short straddle strategy.

This figure shows the payoff chart of a straddle strategy (on the right-hand side of the chart) relative to possible stock price paths of SEO firms following issuance. The short straddle strategy becomes more profitable as the volatility of the SEO firm decreases.

Our analysis begins one day after the SEO event, and ends one month after it[10]. In Figure 2, this period is marked by two dashed vertical grey lines. At the beginning of this period, we note that realised volatility is higher than implied volatility. This suggests that implied volatility, which is a thirty-day forecast of realised volatility, ultimately anticipates a decrease in realised volatility. At the end of the period, we note that realised volatility has decreased, but more dramatically than the option markets expected. Thus, we predict that a volatility trading strategy speculating on a decrease in volatility for this time period could be (significantly) profitable.

Based on the observations in Figure 2, we test the hypothesis that a short straddle portfolio formed on the day after the SEO event (Date + 1) and closed one month after it (Date + 31) is profitable. This volatility trading strategy is illustrated in Figure 3.

Figure 3 shows the payoff profile of a straddle in relation to possible stock price paths of SEO firms. On the left-hand side of the chart, the stock price is simulated for the thirty calendar days following the SEO announcement. We short an ATM straddle on the day following the announcement (Date + 1), and close the position thirty-one calendar days afterward (Date + 31). To obtain a short straddle position, we sell an ATM call and an ATM put with the same strike, underlying, and expiration date, and obtain an option premium from the option buyer as insurance against any price

[10] In an unreported robustness test, we analyse short straddle returns for the period beginning one month after the SEO date and ending two months after issuance. Consistent with our observations in Figure 2, this straddle strategy was not profitable, presumably because option markets have processed the new information and can thus predict future realised volatility on average nearly correctly.

increases (call option) or decreases (put option) of the underlying equity (SEO firm). The straddle position is profitable when the option premium obtained at Date + 1 is higher than the amount to be paid if the call or put option is exercised. The right-hand side of the chart illustrates this idea through the commonly known payoff profile of a straddle position.

If the stock price of the SEO firm increases (decreases) significantly («high volatility»), the call (put) buyer will exercise the ITM position, and the short straddle will have a negative payoff (see shaded areas A and C of Figure 3). If the price of the SEO firm remains principally unchanged («low volatility»), the options will not be exercised, or the exercise of the call (put) will not lead to high payments for the straddle seller. The option premium obtained at Date + 1 is thus higher than the payouts obtained from the exercise of the call/put positions (shaded area B).

Note that, when option markets anticipate risks correctly, we expect the option premiums obtained for selling the call and put options at Date + 1 to be generally the same as the cost to pay when they are exercised at Date + 31. When our hypothesis is supported, and option markets overestimate risks or price options at a risk premium following SEO announcements, we generally expect the option premiums to be higher than the average option payouts, thus generating a trading profit. Therefore, by selling the «expensive» options, we expect the option premium obtained at Date + 1 to be higher than the cost of exercising the options at Date + 31. And the costs of exercising one of the two options will be low if the closing price of the SEO firm at Date + 31 is close to its original price at Date + 1 («low volatility»).

Note further that, in Figure 2, we observed an increase in implied volatility between Date + 1 and Date + 31. This observation may initially seem to contradict our hypothesis that a short volatility strategy for the same time period is profitable. However, this assumption is misleading, because, for straddle return calculations, we only need option market information at Date + 1 when we are forming the portfolio, not at Date + 31 when closing the position. The closing price is the terminal payoff of the options, and it is determined by the stock price, not by option prices or by volatilities at Date + 31. Therefore, the implied volatility or the option prices on the closing date are actually irrelevant for the return calculation, because they would bias the results by reflecting market expectations for the following thirty days (Date + 61), not the past thirty days.

As the reference beginning price, we take the price of the standardised ATM call and put options with expiration dates of exactly thirty days; as the reference closing price, we take the terminal payoff of these options[11]. We follow Coval and Shumway (2001), and use raw net returns rather than logarithmic returns, because options held to maturity can have net returns of –100% (i.e., expire worthless), and the log transformation of –1 is not defined.

[11] The terminal payoff for a call position is max(S-K; 0); for a put position, it is max(K-S; 0). S is the closing price of the underlying equity, and K is the strike price of the option. OptionMetrics sets the theoretical price of standardised options equal to the midpoint of the best closing bid price and best closing offer price for the option.

4.2 Raw returns

In this subsection, we analyse the raw returns from the short straddle strategy for different industry groups. We first calculate the return of a long straddle position held to maturity as follows:

$$
\begin{aligned}
(2)\qquad \mathrm{R}_{\text{long}} &= \frac{str_1^{0,1}}{str_0^{0,1}} - 1 = \frac{c_1^{0,1} + p_1^{0,1}}{c_0^{0,1} + p_0^{0,1}} - 1 = \\
&= \frac{\max(S^1 - K; 0) + \max(K - S; 0)}{c_0^{0,1} + p_0^{0,1}} - 1 = \frac{|S^1 - K|}{c_0^{0,1} + p_0^{0,1}} - 1
\end{aligned}
$$

where S^1 is the price of the underlying asset at Period 1, K is the strike price, and $c_i^{a,T}$ and $p_i^{a,T}$ are the price of a call and put, respectively, on date i (Period 0) that was first in the market at date a (Period 0) and expires at date T (Period 1).

In a second step, we argue that, in a frictionless market, holding both long and short positions for the same position over the same time period should lead to a zero return:

$$(3)\qquad (1 + \mathrm{R}_{\text{long}}) \text{ x } (1 + \mathrm{R}_{\text{short}}) = 1.$$

Based on this relation, we calculate the return of the short straddle position as follows:

$$(4)\qquad \mathrm{R}_{\text{short}} = \frac{1}{(1 + \mathrm{R}_{\text{long}})} - 1.$$

The results are summarised in Table 2. We observe that the volatility trading strategy supports our observations in Figure 2, that the volatility implied from option markets is too high compared to realised volatility. By selling straddles on the day after an SEO event, and closing one month after the announcement, the volatility trading strategy obtains positive raw returns of about 7.4% per month. When we differentiate among industry sectors, however, we observe that equity offerings in mineral industries exhibit the largest average straddle returns (13.1%), and those in the transportation/communications industries exhibit the lowest (2.7%). We also observe that the straddle returns are all positive across industry sectors, indicating qualitatively that our sample firms are similarly affected.

Moreover, we note that the raw straddle returns of matched firms are also positive. However, they are substantially lower than those for SEO firms. As we see in the next subsection, this result can be almost fully explained by common risk factors. As a first robustness check, we find a statistically significant about 4% per month return for a long/short portfolio consisting of a long straddle portfolio of matched firms (short straddle return of 3.54%[12]) and a short straddle portfolio of SEO firms (7.39%) (see Table 2). Because the matched firms have virtually the same firm characteristics as the SEO firms,

[12] The short straddle return of matched firms can be transformed to long straddle returns by using Equation (3).

Table 2: Returns of short straddle portfolios following an SEO event

	Monthly Raw Return (%)	Sample Size
Total	7.39	1,753
Mineral Industries	13.05	133
Construction Industries	3.44	20
Manufacturing	7.30	821
Transportation, Communications	2.70	189
Wholesale Trade	7.09	72
Retail Trade	8.77	107
Service Industries	7.64	406
Others	–	5
Matched Firms	3.54	1,753

This table shows average monthly returns and the sample size of short straddle portfolios formed beginning one day after the SEO event (Date + 1) to one month after the SEO event (Date + 31). Average returns are reported for different industry groups and matched firms. We do not report average returns for the industry groups «Agriculture, Forestry, Fisheries» (SIC = 01xx-09xx) or «Public Administration» (SIC = 91xx-97xx) because of the small sample sizes. Matched firms are matched by firm size and industry classification.

the long/short portfolio's return should not be driven by common market risk factors but by the equity offering.

In the next subsection, we follow standard financial literature and calculate risk-adjusted straddle returns to determine whether the positive returns are «abnormal», or the result of common risk factors.

4.3 Risk-adjusted returns

This subsection describes our econometric framework, which involves estimating the excess returns of the straddle portfolios after correcting for common risk factors. As per previous work in financial economics, we calculate risk-adjusted returns using the three Fama and French (1993) factors, the Carhart (1997) momentum factor, and the Coval and Shumway (2001) volatility factor. The volatility factor is computed by taking the excess return on a zero-beta S&P 500 index ATM straddle. Zero-beta index straddles combine long positions in calls and puts that have offsetting covariances with the index.

Coval and Shumway (2001) define the return of a zero-beta index straddle as:

$$r_{straddle} = \frac{-c\beta_{call} + s}{p\beta_{call} - c\beta_{call} + s} r_{call} + \frac{p\beta_{call}}{p\beta_{call} - c\beta_{call} + s} r_{put} \tag{5}$$

where $r_{straddle}$ is the straddle return, r_{call} and r_{put} are the call and put option returns, c and p are the call and put option prices, and S is the level of the S&P 500 index. Furthermore, β_{call} is the call option delta, which is calculated by using the Black-Scholes (1973) beta, defined as:

$$\beta_{call} = \frac{s}{c} N\left[\frac{\ln\left(\frac{s}{K}\right) + \left(r - d + \frac{\sigma^2}{2}\right)t}{\sigma\sqrt{t}}\right]\beta_s \tag{6}$$

where $N[.]$ is the cumulative normal distribution, K is the exercise price of the call option, r is the risk-free short-term interest rate[13], d is the dividend yield for S&P 500 assets, σ is the standard deviation of S&P 500 returns, and t is the option's time to maturity.

In addition to the common risk factors, we control for firm characteristics. We adjust for skewness with the Harvey and Siddique (2000) skewness factor, and account for differences in the size of proceeds by constructing a variable, «Prosize», which we define as:

$$\text{Pr osize} = \frac{\text{Value of Pr oceeds}}{\text{Market Capitalisation}}. \tag{7}$$

Note that the issuance of new equity (holding debt levels constant) intrinsically reduces leverage, and this effect increases with the SEO proceeds. This reduction in leverage is generally accompanied by a decrease in equity volatility, because of, e.g., lower bankruptcy risk. The connection plays a pivotal role in various contexts. For example, when estimating a company's beta coefficient in a regression framework for a period that includes an SEO, the returns before exhibit a clearly different risk profile than the returns afterward. Given that, the resulting estimated beta coefficient is most likely biased (see, for example, changes in the volatility dynamic before and after the SEO in Figure 2).

However, those relationships do not affect the calculation of our straddle returns. We begin calculating the straddle return on the first trading date after the SEO event. To elaborate, we use the option-implied volatility on the first trading date after the SEO event (market participants are aware of the SEO), and then «compare» it with the realised volatility for the subsequent month.

We cannot rule out a priori any relationship between the relative size of the SEO and the ambiguity premium caused by information intangibility. Following Autore, Bray, and Peterson (2009), SEO announcement company statements about the intended use of proceeds are fuzzy, which, in line with Epstein and Schneider (2008), could be interpreted as low information quality[14]. One could argue for the presence of a negative correlation between relative SEO size and information quality, which could be related to the straddle returns. This is why we include Prosize as an independent variable.

Table 3 reports the estimated parameters from the regression analysis. Regression (1) shows that the variables that adjust for firm characteristics have very limited effects on the straddle portfolio return. Regression (2) shows the regression results for the common risk factors. The straddle portfolio has negative loading on the volatility factor, the momentum factor, and on two of the Fama and French (1993) factors («Mkt-RF» and «SMB»). The loading on the HML factor is positive but not significant.

[13] For the short-term interest rate, we use the BBA Libor one-month rate from Bloomberg.

[14] The majority of firms tend to be vague, and state only that the funds will be used for general corporate purposes. Autore, Bray and Peterson (2009) investigate the relationship between seasoned equity issuers' stated intended use of proceeds, and their subsequent long-run stock and operating performance. We do not control for the use of proceeds within our analysis, however, because SDC provides somewhat unclear statements on their use (this is true for more than 80% of our sample). If we follow Autore, Bray and Peterson (2009), who observed the same pattern in the SDC, and exclude these issuers from our analysis (to avoid the ambiguity over the intended use of proceeds), the resulting sample is too small to draw meaningful conclusions. We use an alternative approach instead, and implicitly assume that the size of the proceeds correlates with information tangibility.

Even more interesting is the fact that alpha, which can be interpreted as the ambiguity premium to the factor model, remains positive and significant (5.94% per month – Regression (2)). When we control for both risk factors and firm characteristics in Regression (7), the straddle return decreases slightly to 5.37% per month, which is still clearly positive and statistically significant.

However, as outlined in the introduction, the ambiguity premium should not have the same expected mean even if the SEO announcements of two firms are equal (e.g., same signal quality). This is because market participants require higher compensation (ambiguity premium) for low signal quality when a firm's fundamental data is more volatile (*intangible*). The demanded ambiguity premium will be small or actually zero even if the signal is ambiguous. In contrast, given low signal quality, market participants will demand increasing ambiguity premiums for firms with more volatile or *intangible* fundamental data.

Epstein and Schneider (2008) argue that the skewness of the return distribution is a suitable measure for the relative importance of tangible and intangible information. They posit that it will be lower for firms with relatively more intangible information, which makes any judgment about the SEO event more difficult. This relationship implies a negative correlation between the ambiguity premium and skewness. To test this relationship, we calculate skewness as a measure of information tangibility for all stocks (1,753) in our sample prior to the SEO event.

Based on the skewness estimated for twelve months prior to the event, we group the stocks into quartiles in ascending order. Q1 represents the quartile of stocks with the lowest skewness («most negative»); Q4 represents the quartile with the highest skewness («most positive»). Based on previous arguments, we expect stocks with the lowest skewness («most negative») to have the highest ambiguity premium in response to the SEO event, as proxied for by the risk-adjusted alphas. However, there is no single best way to implement this. And, although we tried several alternatives, all showed highly similar results (the estimation period for the skewness based on daily returns over three-, six-, nine-, and twelve-month periods prior to the SEO event, and for terciles, quartiles, and ten quintiles). We show here only the results for the twelve-month estimation period and for the quartiles (the others are available from the authors upon request).

In line with the idea that relatively more intangible information is related to higher ambiguity premiums, we find that risk-adjusted alphas (as proxies for the ambiguity premium) are highest for the first quartile (about 30%), in which stocks with the lowest skewness are grouped and the risk-adjusted alphas decline monotonically from Q1 to Q4 (see Regressions (3)-(6) in Table 3). Furthermore, we find that the ambiguity premium is statistically not different from zero for the quartiles with comparably high skewness (Q3 and Q4). This result is also in line with Epstein and Schneider's (2008) theoretical argumentation that the ambiguity premium is low or even zero (statistically insignificant alphas for Q3 and Q4) for companies with predominantly tangible information, even if the SEO announcement itself is intangible.

Finally, we want to analyse if this effect is related to the SEO event, or if it is related to, e.g., industry dynamics. To do so, we report the loadings and «alpha» for the matched-firm straddle portfolio (see Table 3, Regression (8)). The alpha here, as expected, is close

Table 3: Risk-adjusted return calculations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
			Q1	Q2	Q3	Q4		
Sample Size	1,753	1,753	437	437	437	436	1,753	1,753
Alpha	6.29	5.94	30.21%	13.83%	−4.63%	−4.01%	5.37	0.38
	(2.09)	(2.69)	(3.71)	(1.68)	(−0.84)	(−0.52)	(1.68)	(0.13)
Prosize	1.32		−4.19	−1.68	1.86	1.74	1.02	−0.05
	(0.94)		(−1.12)	(−0.41)	(0.93)	(0.44)	(0.73)	(−0.04)
Skew	1.12		1.77	−0.70	−5.48	0.70	−1.13	−0.89
	(1.81)		(1.00)	(−0.37)	(−3.07)	(0.37)	(−1.23)	(−0.95)
Coval-RF		−0.10	−0.01	−0.06	−0.19	−0.20	−0.10	−0.13
		(−3.65)	(−0.14)	(−1.03)	(−2.95)	(−3.03)	(−3.53)	(−4.55)
Mkt-RF		−1.46	−1.51	−2.42	−3.49	1.22	−1.62	0.20
		(−3.00)	(−1.59)	(−2.43)	(−3.11)	(1.22)	(−3.23)	(0.39)
SMB		−0.06	0.35	−1.84	0.63	−1.46	−0.46	−0.04
		(−0.13)	(0.29)	(−1.66)	(0.59)	(−1.4)	(−0.87)	(−0.06)
HML		0.41	−1.62	0.33	6.01	−0.83	1.03	2.32
		(0.62)	(−1.15)	(0.21)	(3.37)	(−0.47)	(1.27)	(2.73)
Mom		−0.02	−1.22	−1.07	1.40	0.48	−0.18	0.79
		(−0.04)	(−1.61)	(−1.26)	(1.6)	(0.53)	(−0.45)	(1.89)

This table shows monthly returns of a short straddle portfolio adjusted with a five-factor model that uses the three Fama-French (1993) factors («Mkt-RF», «SMB», and «HML»), the Carhart (1997) momentum factor («Mom»), and the Coval and Shumway (2001) volatility factor («Coval-RF»). In addition, the returns are controlled for different sizes of proceeds – we use the variable «Prosize» to denote the value of proceeds divided by the market cap – and the Harvey and Siddique (2000) skewness factor («skew»). Our return analysis is conducted for the period beginning one day after the SEO event and ending one month afterward. The first row gives the coefficients, while the second row gives the t-statistics (Newey and West, 1987) in parentheses. The dependent variable is the return of interpolated options with expiration dates of exactly thirty days. Regression results for the industry groups «Agriculture, Forestry, Fisheries» (SIC = 01xx-09xx), «Construction Industries» (SIC = 15xx-17xx), «Wholesale Trade» (SIC = 50xx-51xx), and «Public Administration» (SIC = 91xx-97xx) are not reported due to small sample sizes (less than 100 observations). Regressions (1) and (2) show straddle returns of SEO firms not including all controlling variables, and Regression (7) shows the results when all controlling variables are considered (full model). Regression models (3)-(6) show the results for full models, while (3) represents the quartile of stocks with the lowest skewness (negative) (Q1) and (6) represents the quartile with the highest skewness (positive) (Q4). Regression (8) shows straddle returns of matched firms (matched by *modified* Lyon, Barber and Tsai (1999)-matching).

to zero and also not statistically different from zero. This indicates that the positive raw return for matched firms can be almost fully explained by common risk factors[15].

However, the observed alpha could also have other explanations, namely, differences in time horizon, traded option, or (il)liquidity as an alternative measure for skewness or a source of estimation problems. Those alternative explanations are addressed in the subsequent section.

4.4 Robustness checks

As a first robustness test, we analyse the return of straddle portfolios for a longer time horizon than one month. Following the observations in Figure 2, and our hypothesis of profitability due to short-term related ambiguity premiums, we expect that these straddle strategies will not be profitable. We thus calculate straddle returns for the period beginning one day after the SEO date and ending two months after issuance. We then compare the

[15] In untabulated results, we added the return of the matched firm to our Regressions (1), (2), and (7) in order to implicitly control for firm characteristics and risk factors. We find that the abnormal return is still high and significant. Tables are available from the authors upon request.

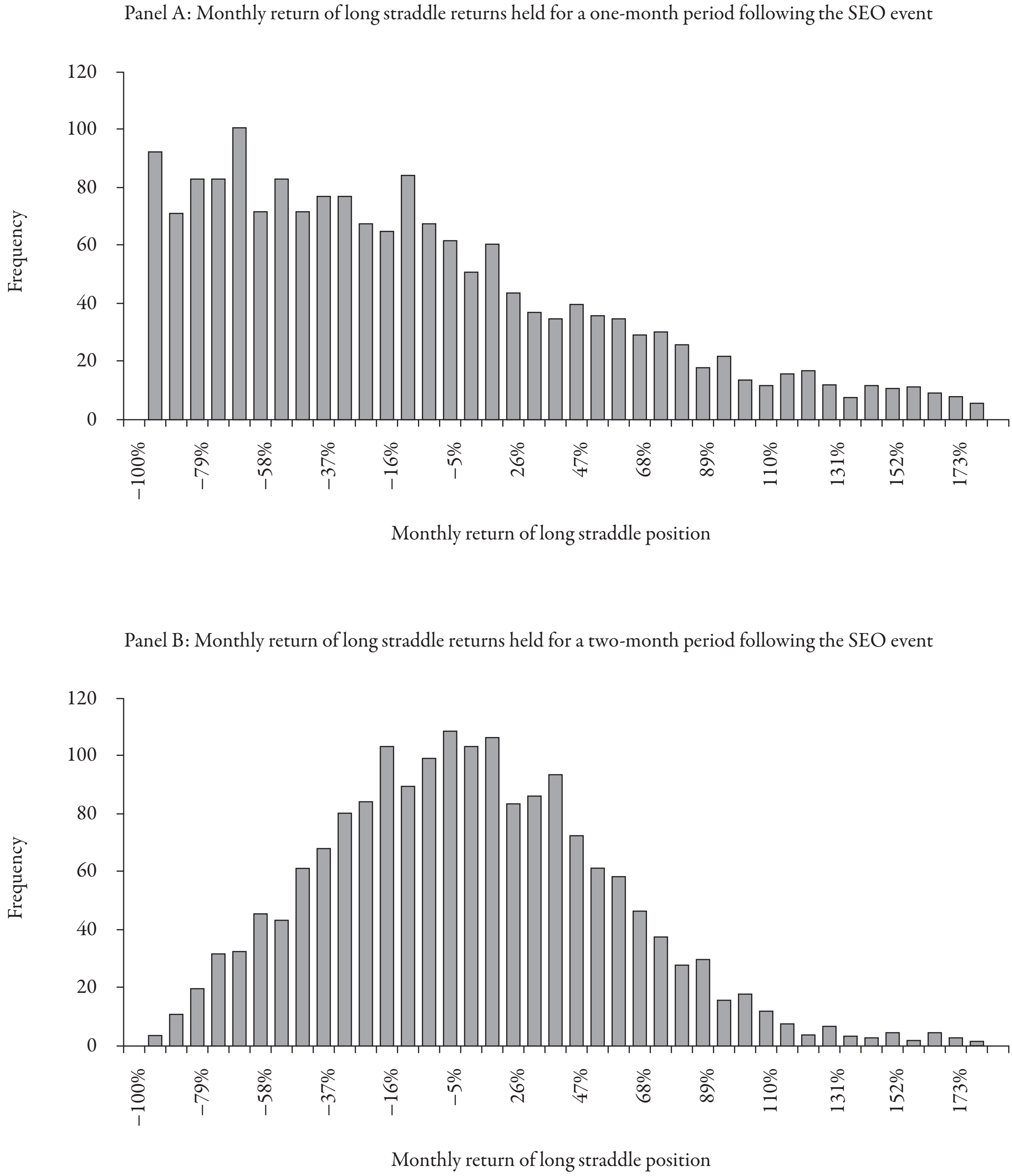

Figure 4: Comparing straddle strategy returns for different time horizons.

This figure shows the histogram of returns of long straddle returns. Panel A shows monthly returns of long straddle returns held for a one-month period following the SEO event; panel B shows monthly returns of long straddle returns held for a two-month period following the SEO event.

histogram of returns between the initial strategies with the short-term horizon with this longer-term (two-month) horizon. The results are summarised in Figure 4.

In panel A of Figure 4, we observe that thirty-day returns of long straddles are clearly skewed to more negative returns (indicating the profitability of shorting the positions). In contrast, «long-term» returns (two-month) are more normally distributed, with no clear indication of direction (panel B, Figure 4). Consistent with our observations in Figure 2, this straddle strategy over a longer horizon is not statistically significantly profitable, because the option markets have already processed the new information of the SEO event and thus no ambiguity premium is found thereafter.

As a further robustness check, we recalculate the returns of the volatility trading strategy for the same short-term period, but this time using traded rather than standardised option data[16]. For the return calculation, we use traded call and put options that expire the following month, and have expiration dates no longer than thirty calendar days. To avoid the maturity mismatch problem in Figure 1, we hold all options to maturity, which implies that the option returns for each SEO event will represent different returns over one month (i.e., the options of security X have twenty days to maturity; the options of security Y have twenty-eight days to maturity; and so on).

By averaging these returns, we obtain an average time to maturity of twenty-five calendar days, which is slightly less than one month. This methodology is different from the analysis used with the standardised dataset, where all options had thirty days to maturity. As a reference beginning price here, we take the average of the closing bid and ask quotes of traded ATM call and put options with expirations in the following month; as a reference closing price, we use the terminal payoff of the options.

Coval and Shumway (2001) used a similar method to calculate option returns. They used options with between twenty and fifty days to expiration to analyse the behaviour of ATM options with one month to maturity. We chose to take average returns for a time period of no longer than one month, because we believe the results could be skewed otherwise[17]. Table 4 shows the raw and risk-adjusted returns for this alternative straddle return calculation methodology, and compares the results with those in Table 3.

Table 4 shows that the sample size is much smaller than that of the standardised option data (290 as opposed to 1,753)[18]. This difference can be largely explained by two restrictive filter criteria. First, the traded option data consist of only traded options (with open interest larger than zero), while the standardised option data have no such restriction. Second, the traded options are required to be ATM at the portfolio formation date. This is not the case for all traded options. The standardised option data are created to be ATM, even though this option does not exist in the market[19].

[16] For a detailed description of the matching procedure and the filter criteria for the CRSP and OptionMetrics datasets, see Goyal and Saretto (2009) and Cremers and Weinbaum (2010). Consistent with Goyal and Saretto (2009), we use the midpoint price as a reference. For robustness, we also used the bid price, and we find qualitatively stable results when controlling for common risk factors. A detailed table is available from the authors upon request.

[17] In panel A of Figure 2, we note that, before the end of our trading period (illustrated by two vertical dashed grey lines), volatility drops sharply. After the end of the period, it begins to increase immediately. Using periods longer than thirty days could mean including the effects of the increase in volatility after thirty days, and thus skew our results. When we split the sample of straddles that expires before and after the thirty-day time period, we find that short straddle positions with options that expire before thirty days have a 7.39% average return (as reported in Table 4); those with options that expire between thirty and fifty days have a 0.8% average return (not tabulated).

[18] Due to the small sample size, we do not differentiate among different industry sectors.

[19] At-the-money (ATM) options are defined as those with strike prices within 5% of the current stock price. See, for example, Chakravarty, Gulen, and Mayhew (2004) and Battalio and Schultz (2006). Note that our traded option sample would not increase significantly if we ease the ATM criteria, because most of the options are filtered out due to zero open interest, which is the main criterion of traded options.

Table 4: Risk-adjusted return calculations with traded option data

	Traded Option Data	Standardised Option Data
Raw Return	7.39	7.38
Sample Size	290	1,753
Alpha	7.35	5.37
	(1.04)	(1.68)
Prosize	–2.84	1.02
	(–1.08)	(0.73)
Skew	–3.78	–1.13
	(–1.87)	(–1.23)
Coval-RF	–0.17	–0.10
	(–2.48)	(–3.53)
Mkt-RF	–0.55	–1.62
	(–0.47)	(–3.23)
SMB	–0.86	–0.46
	(–0.64)	(–0.87)
HML	2.77	1.03
	(1.47)	(1.27)
Mom	0.01	–0.18
	(0.01)	(–0.45)

This table shows monthly returns of a short straddle portfolio adjusted with a five-factor model that uses the three Fama-French (1993) factors («Mkt-RF», «SMB», and «HML»), the Carhart (1997) momentum factor («Mom»), and the Coval and Shumway (2001) volatility factor («Coval-RF»). In addition, the returns are controlled for different sizes of proceeds – we use the variable «Prosize» to denote the value of proceeds divided by the market cap – and the Harvey and Siddique (2000) skewness factor («skew»). In the first column, we use traded option data to calculate straddle returns («Traded Option Data»). Our return analysis is conducted for the period beginning one day after the SEO event and ending one month afterward. The dependent variable is the return of straddle portfolios with average expiration dates of twenty-five days. The second column duplicates the results from Table 3, where standardised option data was used to calculate straddle returns («Standardised Option Data»). The first row gives the coefficients; the second row gives the t-statistics (Newey and West, 1987) in parentheses.

Despite the smaller sample size, the results in the first column of Table 4 («Traded Option Data») are consistent and similar to our standardised option data analysis. Straddle returns calculated using traded option data lead to a 7.39% average raw return over a twenty-five-day period, which is almost identical to that reported for the standardised option data. By considering common risk factors, we obtain an unexplained alpha of 7.35% for the twenty-five-day period, which is even higher than the alpha reported for the standardised option dataset (5.37% for a thirty-day period).

In our final robustness check, we control for the influence of liquidity on our results. If a stock's liquidity is low, as measured by, e.g., trading volume, the stock price can change substantially even without news events, and can potentially cause substantial fluctuations in stock volatility. As a result, volatility models built on those stocks have a high chance of being «fragile», and could cause estimation problems. The following points provide evidence that our results should not be effectively affected by illiquidity issues.

1. The stocks considered in the analyses are comparably large, because offering options typically correlate with company size. Therefore, the trading volume of those stocks is not expected to shrink after the SEO event to such low levels as to render volatility estimations «meaningless». Furthermore, we use the stock returns over the one-year period prior to the SEO event in order to calculate the skewness for the subsequent sorting and obtain an indication of the ratio between tangible and intangible information (see again Table 3). The skewness calculation is clearly based on trading volume before the SEO event, which is therefore not affected by potential liquidity changes in response to the SEO event.

2. To calculate the straddle returns in Table 3, we use standardised option data from OptionMetrics[20]. Standardised options are only included in OptionMetrics if option liquidity is sufficiently high. Thus, given the careful treatment of illiquid options by OptionMetrics, we are confident that the implied volatilities we obtain from using their standardised options are not driven by any estimation problems.

3. We include put and call option volume, as well as the open interest of call and put options at the event day, as controlling variables in the multivariate regression for the calculation of the risk-adjusted returns. We find that neither controlling variable is statistically significantly different from zero. Extending the arguments in (2), we do not find any evidence that illiquidity is a driver of estimation problems, because the results are very similar to those without the inclusion of the two liquidity measures (see Table 5, panel A for volume, and panel B for open interest as proxies for illiquidity). In untabulated results, we also check whether any of the effects change when using call and put volume and open interest jointly. The results look virtually identical.

4. We calculate the option market volume and open interest around the SEO event and find they are highest at the event date, while they decline afterward[21]. In other words, liquidity is highest on the event date when we form our straddle strategy. Therefore, the results are arguably least affected by illiquidity on the date the strategy is set up. We also hold the options until expiration (cash settlement). Therefore, the returns are not affected by any illiquidity issues from closing out of the straddle.

5. Furthermore, the previous robustness check, when we investigate whether the straddle returns using standardised option data mirror actual traded options, reveal that the average raw straddle returns of 7.39% for traded options are almost identical to the 7.38% found for the standardised options. If illiquidity was influencing the option-implied volatilities of the standardised option, we would expect the raw returns of both calculation methods to look different.

To summarise, we are convinced our results are not driven by any estimation problems caused by illiquidity because 1) we focus on rather large companies, 2) standardised option data is only available if enough option price data is available, and, finally, 3) we find that raw straddle returns for traded options are almost identical to those obtained from traded option data.

However, Ozsoylev and Werner (2011) and Xia and Zhou (2014) show a relationship between liquidity and ambiguity, and use liquidity measures such as volume as an alternative to skweness. To test for any link, we again refer to the regression results obtained when both option volume and option open interest at the SEO event were included (see Table 5, panels A and B). It is clear that both measures have only a negligible influence on the results, and that the results are similar to those without liquidity measures. Note that, when creating subsamples for skewness quartiles, the liquidity measures are not statistically significant, and alphas are similar to those in Table 3.

[20] OptionMetrics notes in their manual that «[a] standardized option is only included if there exists enough option price data on that date to accurately interpolate the required values».
[21] Figures are available from the authors upon request.

Table 5: Risk-adjusted return calculations with control variables for liquidity

Panel A: Call and put option volume as controlling variables for liquidity

	All	Q1	Q2	Q3	Q4
Sample Size	1,684	427	421	418	418
Alpha	4.10	29.89	11.75	−6.07	−6.00
	(1.26)	(3.55)	(1.38)	(−1.09)	(−0.75)
Prosize	1.24	−4.15	−1.27	2.13	2.42
	(0.88)	(−1.1)	(−0.3)	(1.05)	(0.6)
Skew	−1.12	1.77	−0.78	−5.42	0.71
	(−1.22)	(1)	(−0.41)	(−3.03)	(0.37)
Coval-RF	−0.10	−0.01	−0.06	−0.20	−0.20
	(−3.56)	(−0.14)	(−1.02)	(−3.07)	(−3.01)
Mkt-RF	−1.62	−1.51	−2.35	−3.55	1.19
	(−3.24)	(−1.58)	(−2.35)	(−3.15)	(1.19)
SMB	−0.48	0.36	−1.83	0.48	−1.57
	(−0.91)	(0.3)	(−1.65)	(0.45)	(−1.49)
HML	1.03	−1.61	0.51	5.74	−0.81
	(1.27)	(−1.14)	(0.31)	(3.19)	(−0.46)
Mom	−0.17	−1.22	−1.09	1.27	0.62
	(−0.42)	(−1.6)	(−1.28)	(1.44)	(0.67)
Call Volume	0.02	> 0.00	0.03	0.04	> 0.00
	(1.56)	(0.08)	(1.16)	(1.42)	(0.13)
Put Volume	−0.02	< 0.00	−0.05	−0.05	0.02
	(−1.23)	(−0.02)	(−1.09)	(−1.31)	(0.32)

Panel B: Call and put open interest at the SEO event day as controlling variables for liquidity

	All	Q1	Q2	Q3	Q4
Sample Size	1,684	427	421	418	418
Alpha	4.63	30.55	11.56	−4.76	−5.52
	(1.42)	(3.59)	(1.36)	(−0.84)	(−0.68)
Prosize	1.18	−4.25	−0.92	1.88	2.30
	(0.84)	(−1.12)	(−0.22)	(0.93)	(0.57)
Skew	−1.12	1.78	−0.65	−5.48	0.71
	(−1.22)	(1.01)	(−0.35)	(−3.06)	(0.37)
Coval-RF	−0.10	−0.01	−0.06	−0.19	−0.20
	(−3.57)	(−0.14)	(−1.11)	(−2.94)	(−2.98)
Mkt-RF	−1.61	−1.51	−2.30	−3.50	1.10
	(−3.22)	(−1.59)	(−2.31)	(−3.1)	(1.1)
SMB	−0.47	0.35	−1.84	0.62	−1.57
	(−0.89)	(0.3)	(−1.66)	(0.58)	(−1.5)
HML	1.03	−1.63	0.37	5.98	−0.83
	(1.27)	(−1.16)	(0.23)	(3.31)	(−0.47)
Mom	−0.17	−1.22	−1.16	1.39	0.60
	(−0.43)	(−1.61)	(−1.35)	(1.57)	(0.66)
Call Open Interest	> 0.00	> 0.00	> 0.00	> 0.00	> 0.00
	(1.89)	(0.22)	(1.6)	(0.11)	(1.34)
Put Open Interest	< 0.00	< 0.00	< 0.00	< 0.00	−0.01
	(−1.83)	(−0.25)	(−1.76)	(−0.09)	(−0.98)

This table shows monthly returns of a short straddle portfolio adjusted with a five-factor model that uses the three Fama-French (1993) factors («Mkt-RF», «SMB», and «HML»), the Carhart (1997) momentum factor («Mom»), and the Coval and Shumway (2001) volatility factor («Coval-RF») for quartiles sorted by firms' skewness of their return distributions over the twelve-month period prior to the SEO event. Q1 represents the quartile of stocks with the lowest skewness (negative), and Q4 represents the quartile with the highest skewness (positive). In addition, the returns are controlled for different sizes of proceeds – we use the variable «Prosize» to denote the value of proceeds divided by the market cap; the Harvey and Siddique (2000) skewness factor («skew»). In panel A, we use call and put option volume as controlling variables for liquidity; in panel B, we use call and put open interest at the SEO event day. Our return analysis is conducted for the period beginning one day after the SEO event and ending one month afterward. The dependent variable is the return of interpolated options with expiration dates of exactly thirty days. The first row gives the coefficients, while the second row gives the t-statistics (Newey and West, 1987) in parentheses.

In unreported results, we also conducted a double-sorting among skewness and liquidity (lowest skewness and liquidity quantile) to possibly identity SEO events with the highest expected «alphas». However, those returns were statistically not different from the double-sorted portfolios with lowest skewness and higher liquidity levels. Therefore, we do not believe the liquidity measures calculated at the SEO event day, as proposed by, e.g., Ozsoylev and Werner (2011), have any material impact on the results, or add any additional value to skewness as a measure of information tangibility.

5 Conclusion

We analyse cross-sectional volatility (realised and option-implied) dynamics around SEOs, and show that short-term realised volatility dynamics following SEO event are not fully reflected by option markets. In particular, we find that realised volatility exhibits a strong decrease following an announcement, while the expected volatility implied from option markets remains constant, and thus «overestimates» realised volatility. This significant overestimation of future risk, however, only occurs for the first month following the announcement. Afterward, option markets seem to process the new information and estimate future volatility correctly. Thus, expected volatility implied from option prices is approximately the same as realised volatility, plus some additional risk factors observed by other researchers.

In a further analysis, we examine the extent of investor «misreactions» by analysing volatility trading strategies based on the difference between option-implied and realised volatility. We use short straddle portfolio returns to explore the differences following SEO announcements, which led to significantly positive returns of around 5.5% (after controlling for several common risk factors) for a one-month period. We interpret this as an ambiguity premium, and, in line with Epstein and Schneider (2008), we find it is positively correlated with a firm's fundamental data intangibility, as proxied for by the skewness of stock returns. For subsamples with comparably high skewness, the ambiguity premium was, as expected, not statistically different from zero. But for the subsample with the lowest skewness (highest intangibility of firm fundamental data), the ambiguity premium was statistically significant at about 30%. Therefore, our results fit perfectly into Epstein and Schneider's (2008) theoretical framework. Several robustness checks, where we investigated the influence of different time horizons, liquidity, and traded options, did not alter our results.

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