

The Effect of EPS Estimate Dispersion on Option Implied Volatility and Straddle Price Changes Following Earnings Announcements

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1. Introduction

When firms announce quarterly and annual earnings, they provide information to market participants about their most recent financial performance and often times provide guidance as to their expectations for future performance. These announcements can have varying degrees of impact on market measures like stock price and option implied volatility depending on what market expectations were before the announcement.

When earnings results differ widely from expectations (earnings surprise), it can result in larger changes in market measures because the market must now incorporate a significant amount of information it previously did not have or expect. By similar logic, when there is a large degree of uncertainty built into market expectations, subsequent earnings announcements should also result in larger changes in market measures because the market is no longer incorporating as wide a degree of possible outcomes. This change should be most evident in option implied volatility markets. When there is a heightened level of uncertainty, option implied volatility should reflect this by being at a higher level than normal. If this uncertainty were to be reduced or eliminated, then implied volatility should return to normal. In this paper we test this theory by examining option implied volatility changes in the context of an overnight straddle trading strategy and comparing them to two measures of uncertainty around future earnings expectations. We implement a trading strategy of selling straddles the trading day before earnings announcements and then buying them back the trading day after earnings announcements to determine the profit/loss from these trades, and then compare this profit/loss to the same measures of uncertainty as well as other factors. If the market were perfectly efficient, then the profit/loss for this strategy should be zero

(ignoring bid-offer costs) because the change in implied volatility will perfectly account for the volatility realized on the earnings announcement date. Our results somewhat differ from the previous literature in that we find that these measures of uncertainty have very little explanatory power in our model, and under certain constraints our strategy can yield a positive profit/loss.

It has been well documented in the literature that option prices factor in impending information disclosures. Patell and Wolfson (1979, 1981) were the first to observe this. Using a sample 290 observations between 1976 and 1977, they found that larger stock price changes after earnings announcements were preceded by larger increases in option implied volatilities. Further, they found that implied volatility rose in the days prior to the announcement and dropped immediately afterwards. Donders, Kouwenberg, and Vorst (2000) expanded this research using a dataset of 40 firms listed on the Amsterdam Stock Exchange from 1991 to 1993. They confirmed that option implied volatility increased before announcement days and dropped afterwards. The average overnight drop in implied volatility on announcement days was around 4%. They also found that options trading volume and open interest increases in the days before announcements and concluded based on the data that investors are buyers of options in this period. More recently, Dubinsky and Johannes (2005) use a sample of 20 firms from 1996 to 2002 to model volatility changes around earnings as a jump discontinuity process.

There has been little research comparing option implied volatility changes around earnings announcements to measures of market expectations uncertainty. Ajinkya and Giff (1985) were the first to examine this by comparing the dispersion of sellside analysts' earnings forecasts to changes in volatility using data from 1977 to 1978. They only included observations with at least four earnings estimates and calculated their dispersion measure as the variance divided by the mean (coefficient of variation). For each of the 12 months preceding the announcement date, they regressed the average implied volatility on the dispersion measure as well as the historical realized volatility over the past 50 days. In the month preceding the announcement, they observed a 23% correlation between the dispersion measure and the average implied volatility. However, in the regression model they found the coefficient of the dispersion measure to be insignificant. As one went further back in time though, they found it to be significant. This study suffered from only having an average of 63 observations in each month. Daley, Senkow, and Vigeland (1988) updated this study by adding a second year of data (increasing sample size to 100 firm-years) and further filtering the option volatility information (they separated data for options expiring before and after the announcement date). Their results suggested that the variance in analysts' earnings forecasts is significantly positively related to the implied volatility of options expiring after the announcement date, but not related to the implied volatility of options expiring before the announcement date. However, they suspected the model had misspecification issues because of significant intercept terms in both cases.

2. Methodology

Our study measures the performance of a trading strategy which sells straddles before earnings announcements and subsequently buys them back after the announcement. To do this we used data from January 2002 to June 2007 and compared closing options prices on the trading day before the announcement to prices after the announcement and measured the difference. We then tested various factors to see whether they could identify which options were more profitable to implement this strategy with. These included the degree of market uncertainty around earnings figures as measured by the dispersion of equity analysts' earnings estimates, changes in option implied volatility, option open interest, industry classification, and time.

Before conducting our study, we decided that we needed to select companies with sufficient options trading volume for the results to have any practical trading implications. We suspected that stocks with high option volumes are less likely to be ones with greater earnings estimate variation as they tend to be the largest companies with the greatest and most thorough analyst coverage. This led us to select the set of S&P 500 issuers. Amongst these, we found 475 companies that had sufficient analyst coverage to be included in the study.

To conduct our study, we needed information by company on earnings estimates and volatility implied from options prices. We compiled a panel dataset of earnings and volatility data from two sources, Zacks Investment Research and OptionMetrics. Zacks History Files contain earnings estimates, stock recommendations, and earnings

surprises from 1978 to today. OptionMetrics has detailed daily historical information on publicly traded option chains for a wealth of companies.

When we were gathering earnings estimate histories we considered First Call data as well as Zacks History Files. We opted for Zacks because it seemed to have more recent earnings information for a given reporting period. First Call estimates updates tended to stop about six months before the actual reporting dates. We felt that estimates older than six months were stale and not meaningful for our purposes. Zacks contained much more recent information, including estimate updates which occurred after the Quarter End date but before the reporting date. We decided to eliminate all estimates for each analyst which were 180 days or more before the announcement date, and then take only their most recent estimates. We did not filter for any sort of purported “quality”, ie. the idea that estimates from the major investment banks were more accurate because they are able to hire the most talented analysts. Most estimates tended to be from the major investment banks anyway based on what Zacks provided. Estimates came in two forms, quarterly and annual. We felt that there should be no difference in volatility movements based on this distinction, however for 4th quarter earnings we decided to eliminate the quarterly estimates and keep the annual estimates to prevent double counting issues.

With the earnings estimates for each period for each company, we constructed two measures of dispersion. The first is the absolute value of the coefficient of variation (ACV), calculated in each period as,

$$ACV_i = abs\left(\frac{\sigma_{EE_i}}{\mu_{EE_i}}\right)$$

where σ_{EE_i} is the standard deviation of the earnings estimates for company i , and μ_{EE_i} is the mean of the earnings estimates for company i . This measure suffers from large values when μ_{EE_i} is near 0 which is confounding when, ideally, we want to isolate the effects from σ_{EE_i} only. This led us to consider our second measure of dispersion, the earnings variation to price ratio (EVPR), calculated in each period as,

$$EVPR_i = \frac{\sigma_{EE_i}}{p_i}$$

where σ_{EE_i} is the standard deviation of the earnings estimates for company i , and p_i is the stock price on the day before the period earnings announcement for company i .¹ Our last concern was that both of these measures would be unreliable if there were not a sufficient number of underlying earnings estimates, so we filtered our dataset for only those company-periods in which there were five or more earnings estimates.

¹ We thank Robert McDonald at the Kellogg School of Management for the suggestion.

Our biggest difficulty constructing this dataset was determining the timing of earnings announcements. Companies can announce their earnings before market open (“before the bell”), during market hours, or after market close (“after the bell”) on a given day. Our study wishes to look at changes in volatility before and after earnings announcements relative to earnings estimate variation levels, so getting the timing right is crucially important. For this timing data we turned to Bloomberg. Bloomberg provides accurate historical announcement date information, but historical timing information is not as good. In our final panel set, we had announcement timings from Bloomberg for 83.5% of the sample. For the remainder, we performed a multi-step manual scrubbing process. We first examined each company’s history of timing to detect if there was an obvious pattern. Many companies announce only before the bell or only after the bell. When only a few periods were missing and it appeared to follow an obvious pattern, we filled in the missing data consistent with this pattern. When the pattern was not obvious, we looked to market data to guide us. We started with the premise that stock price and implied volatility change the most immediately after the earnings announcement if one were to look just at the three day window around the announcement. We then examined the market changes from the day before the announcement to the day of the announcement and from the day of the announcement to the day after the announcement and used our best judgment. Since we were dealing with closing market data, we reasoned that announcement during market hours had the same effects as announcements before market hours. When we tested on the dataset, we found that the results using only the subset with Bloomberg provided announcement timings were comparable to the results using the entire sample with the manual data fill.

For all options related data we used OptionMetrics. Their call and put information is specific for a given ticker, a given expiration, and a given strike price. Information available includes closing bid price, closing offer price, volume, open interest, implied volatility, delta, gamma, vega, and theta. They also have a database of “standardized” options which uses all available pricing information for a given ticker on a given date to determine what the implied volatility would be for a 50-delta option with a user-specified time to expiration. We believe OptionMetrics’ methodology is sound and their results are reliable.

We first filtered OptionMetrics database down to the 475 issuers we found had sufficient analyst coverage. We then further filtered this data for each issuer to observations with a market close date immediately before an earnings announcement and observations with a market close date immediately after the announcement. We then needed to pick a specific strike price and expiration to use for the straddle trade. To maximize the effect of a volatility change, we decided to use the at-the-money, front month options. For each expiration, we designated a strike price “at-the-money” if the delta of the corresponding straddle was closest to 0. So, for example, if the straddle with a \$35 strike and 30 days to expiration had a delta of +0.17 and the straddle with a \$40 strike and 30 days to expiration had a delta of -0.23, we would designate the \$35 strike “at-the-money”. On the options trading floor, the “front month” option chain is simply the option chain with the least time to expiration. Using this methodology would not be practical for the purposes of this paper because as time to expiration gets small, options

tend to trade close to parity and are more heavily affected by changes in the underlying stock price. At-the-money options have increased gamma while in-the-money and out-of-the-money options have decreased gamma. Our trading strategy yields the best results if we can isolate the effect on options prices of changes in volatility, so we did not want to include options with too large a gamma. Even though vega increases with time to expiration, implied volatility changes around earnings tend to be less dramatic thereby resulting in greater volatility-change-induced option price movements for front month options. From what we could observe in the data, we felt the effect from delta and gamma of underlying stock price movements outweighed the effect from vega of implied volatility changes as time to expiration got small, so we decided to designate the “front month” option as the one with the least time to expiration greater than one week. To be consistent, we designated the ATM front month option on the day before the earnings announcement and then used the same strike price and expiration for the day after the earnings announcement. The final sample had 8,039 observations between January 2002 and June 2007.

With the volatility and announcement timing data, we constructed two volatility change variables. The first is the change in volatility implied by call options (CIVD), calculated in each period as,

$$CIVD_i = CIV_{i_t} - CIV_{i_{t-1}}$$

where CIV_{i_t} is the ATM front month call option implied volatility immediately following the earnings announcement for company i , and $CIV_{i_{t-1}}$ is the ATM front month call

option implied volatility immediately before the earnings announcement for company i . The second measure follows the same construction except it measures the change in volatility implied by put options (PIVD), calculated in each period as,

$$PIVD_i = PIV_{i_t} - PIV_{i_{t-1}}$$

where PIV_{i_t} is the ATM front month put option implied volatility immediately following the earnings announcement for company i , and $PIV_{i_{t-1}}$ is the ATM front month put option implied volatility immediately before the earnings announcement for company i .²

We also constructed additional variables to measure price changes and liquidity. The first measures the profit or loss in dollar terms of selling one straddle immediately before an earnings announcement and buying it back immediately after (*Straddlepl*), calculated in each period as,

$$Straddlepl_i = StraddleBid_{i_{t-1}} - StraddleOffer_i$$

where $StraddleBid_{i_{t-1}}$ is the bid price of the ATM front month straddle immediately before the earnings announcement for company i , and $StraddleOffer_i$ is the offer price of the ATM front month straddle immediately following the earnings announcement for company i . *ReverseStraddlepl* calculates the dollar profit or loss from the opposite

² On a theoretical level, for Put-Call Parity to hold we would expect these two measures to be equal. In practice, we would expect there to be some difference because the size and position around fair value of the bid-offer can vary between calls and puts for the same strike and maturity. The data shows that these measures do in fact tend to be very close to each other.

trade (buying straddles before earnings and selling them back after earnings). The second measure expresses *Straddlepl* in percentage form, calculated in each period as,

$$Straddleplpc_i = \frac{(StraddleBid_{i_{t-1}} - StraddleOffer_i)}{StraddleBid_{i_{t-1}}}$$

The third measure attempts to control *Straddlepl* for stock price movements. It takes the delta position of the straddle before earnings and hedges it with an equivalent number of shares of the underlying stock. Selling the straddle before earnings could result in either a positive or negative delta position, so the hedge will either sell or buy stock to curb the delta risk (however, the position will still be exposed to negative gamma so it is not a perfect hedge). This measure (*Hedgedpl*), is calculated in each period as,

$$Hedgedpl_i = Straddlepl_i - StraddleDelta_{i_{t-1}} \times (Stockprice_i - Stockprice_{i_{t-1}})$$

where *StraddleDelta_{i_{t-1}}* is the ATM front month straddle delta immediately before the earnings announcement for company *i*, *Stockprice_i* is the closing stock price immediately after the earnings announcement for company *i*, and *Stockprice_{i_{t-1}}* is the closing stock price immediately before the earnings announcement for company *i*. The fourth measure attempts to capture the straddle bid-offer (*TBO*), calculated in each period as,

$$TBO_i = CBO_{i_{t-1}} + PBO_{i_{t-1}}$$

where $CBO_{i,t-1}$ is the dollar bid-offer for the ATM front month call option immediately before the earnings announcement for company i , and $PBO_{i,t-1}$ is the dollar bid-offer for the ATM front month put option immediately before the earnings announcement for company i . All observations with a negative bid-offer were eliminated from the set. Finally, we calculate a measure of open interest for the option strike, calculated in each period as,

$$TOI_i = COI_{i,t-1} + POI_{i,t-1}$$

where $COI_{i,t-1}$ is the open interest for the ATM front month call option immediately before the earnings announcement for company i , and $POI_{i,t-1}$ is the open interest for the ATM front month put option immediately before the earnings announcement for company i .

Next we reasoned that if implied volatility returns to a “normal” level after earnings announcements, then the degree of change might be related to how much it had increased in the time prior to the earnings announcement. To measure this we turned to OptionMetrics’ standardized options database. We created “Implied Volatility Inflation Factors” which take the difference between the implied volatility on the day immediately prior to the earnings announcements and the five day average implied volatility starting

ten trading days before earnings (and ending six trading days before earnings).³ This measure for calls (*CIV Inflation*) is calculated in each period as,

$$CIVInflation_i = StCIV_{i_{t-1}} - \frac{StCIV_{i_{t-6}} + StCIV_{i_{t-7}} + StCIV_{i_{t-8}} + StCIV_{i_{t-9}} + StCIV_{i_{t-10}}}{5}$$

where $StCIV_{i_{t-1}}$ is the implied volatility for the 50-delta call option with 30 days to expiration immediately before the earnings announcement for company i , and each time interval represents one trading day.

To estimate the final model, we used a simple functional form. We made *Straddlepl* and *Straddleplpc* dependent variables in a linear regression with *ACV* or *EVPR* as independent variables, along with controls for *TOI*, *CIVInflation*, *TBO*, and dummies for each year.

$$Straddlepl_t = \beta_0 + \beta_1\{ACV_t, EVPR_t\} + \beta_2TOI_t + \beta_3CIVInflation_t + \beta_4TBO_t + \beta_5d2003_t + \beta_6d2004_t + \beta_7d2005_t + \beta_8d2006_t + \beta_9d2007_t + \varepsilon$$

$$Straddleplpc_t = \beta_0 + \beta_1\{ACV_t, EVPR_t\} + \beta_2TOI_t + \beta_3CIVInflation_t + \beta_4TBO_t + \beta_5d2003_t + \beta_6d2004_t + \beta_7d2005_t + \beta_8d2006_t + \beta_9d2007_t + \varepsilon$$

This compares to the functional forms used in the literature which models the option implied volatility before earnings announcements as a linear combination of the “normal”

³ Given that this measure only accounts for the change in volatility over an approximately one week period, a reasonable hypothesis would be that it should be equal to zero. We, however, hypothesize that investors tend to be more active as it gets closer to earnings announcements and, knowing this, market makers increase volatility levels.

volatility (the average realized volatility for a stock over a short time interval immediately preceding the date the implied volatility was calculated) and a scaled earnings dispersion measure similar to the ones we have constructed.

$$IV_t = \beta_0 + \beta_1 \bar{\sigma} + \beta_2 ACV_t + \varepsilon$$

Conceptually, this construction makes sense because it is comparing option implied volatility levels against their norms. However, this does not provide enough information to determine if it can be used in a trading strategy as it does not specify the time it would take for an earnings estimate dispersion induced abnormal volatility level to return to normal. Our construction, however, looks specifically at an overnight trading strategy. The downside to our construction is that it compares a change variable (*Straddlepl* or *Straddleplpc*) to a level variable (*ACV* or *EVPR*), but we feel the nature of the level variables in this case lend themselves to comparison with change variables because of the scaling used.

3. Results

We analyzed the results from the 475 companies at three levels: an aggregate basis, by year of earnings announcement, and by two-digit GICS Sector codes (see Appendix 1).

On an aggregate basis, we found the average changes in call implied volatility and put implied volatility immediately following earnings announcements to be -3.51% and -3.46%, respectively (see Table 1). As suspected, on average there was an increase in

call implied volatility over the week prior to earnings, but only 1.47%. The average loss for writing straddles before earnings and then buying them back after was \$0.28 per straddle, or 11.7%, which is approximately the size of the average bid-offer, \$0.29 per straddle. The average *Hedgedpl* is even lower. This implies that randomly executing this trading strategy would result in a wash between winners and losers before transaction costs. This result is consistent with what market efficiency theories would predict. So, in order for a profitable trading strategy to emerge there needs to be enough explanatory power introduced to more than compensate for the straddle bid-offer and other fees/commissions.

Next we looked at a simple correlation matrix containing the variables (see Table 2). We found a near 0 correlation between *ACV* or *EVPR* and *CIVD* or *PIVD*. The correlation was also very low for *Straddlepl* or *Straddleplpc*. The largest correlations were between *CIVD* or *PIVD* and *Straddlepl* or *Straddleplpc*, indicating that the ability to predict changes in implied volatility should lead to a profitable trading strategy. The other points of interest were the moderate correlations between *Straddlepl* or *Straddleplpc* and *TOI*, as well as *Straddlepl* or *Straddleplpc* and *CIVInflation*. To test for significance, we ran regressions with these variables (see Table 3). Neither *EVPR* nor *ACV* were significant in predicting P&L, however both *TOI* and *CIVInflation* were highly significant. There were also some interesting yearly effects, with more recent years appearing to yield higher profits than previous years. Looking into this further, we discovered that there was a correlation between Open Interest and Year. After running separate regressions for each year, both *TOI* and *CIVInflation* were highly significant.

With this information we decided to see how average profits changed with varying degrees of Open Interest and CIV Inflation. To do this, we created mean statistics for P&L figures conditional on a given level of *TOI*, *CIVInflation*, or both (see Table 4). These cutoffs were calculated for each variable by rank ordering the variable over the entire sample and separating the observations by different percentiles. For example, a 25% cutoff for *TOI* only uses observations whose *TOI* value falls into the top 75% of the sample. A 99% cutoff uses observations in the top 1% of the variable. Using this method for *TOI* is somewhat problematic because Open Interest seems to be increasing with time, but even with this method there did not appear to be an extraordinary number of observations in more recent years for high *TOI* cutoffs. What is interesting is the power of Open Interest information. By simply using observations in the 95th percentile, on average one can generate enough P&L from the straddle trades to more than cover the bid-offer. If one were to combine the Open Interest information with the CIV Inflation information, then one can generate average *overnight* profits of \$0.23 per straddle, or nearly 10%. This is incredibly powerful. It is apparent that these observations have very large *CIVD* and *PIVD* values, which helps explain why they yield such profitable trades. We also calculated a “hit-rate” table to see how often the straddle trade was profitable (see Table 5). Note that for 90th percentile Open Interest, the negative returns are heavily skewed by an outlier \$2.80 (63%) loss in 2002. Delta hedging would have lowered the loss to \$1.64 (37%). We have no concrete theory as to why options with large open interest have higher changes in implied volatility after earnings announcements. We suspect it is an effect of supply and demand fundamentals.

Investors are more likely to be buyers of options than sellers, and contracts with large open interest are possibly a result of extraordinary demand, so the combination of these two effects causes market makers to increase implied volatility more than normal to collect a higher option premium.

An examination by year shows that *CIVD* and *PIVD* are increasing with time, which helps explain why the more recent years yielded more profitable trades on average (see Table 6 and Figure 1). It is worth noting that the percentile cutoffs for *TOI* and *CIVInflation* seem to add incremental P&L information somewhat consistently over time. Only when one gets to the 95th percentile or above does it become highly inconsistent, but this is most likely due to the declining sample size adding noise. Examining the average P&L using both *TOI* and *CIVInflation* cutoffs by year shows there is a decent amount of variation over time. Comparing the *Straddlepl* means against the *Hedgedpl* means, one can see that delta-hedging the position reduces some of this variability. The hedge tends to win when the straddle trade loses money, and the hedge tends to lose when the straddle trade wins money. This would suggest that stock price movements and the effect of delta and gamma are more likely to prevent the straddle trade from being profitable than insufficient moves in implied volatility. The *Hedgedpl* figures do not account for transaction costs, but since the Open Interest cutoffs reduce the sample space to highly liquid, heavily traded issuers, we suspect they would be small. The Absolute Value of the Straddle Delta indicates how many shares would be necessary to hedge one straddle. It is also possible to select opportunities based on

the straddle delta and limit them to ones where the delta is small so that hedging becomes less share intensive.

Lastly, we looked at potential industry effects on P&L. We did not observe any industry effects of note over the entire sample. However, after conditioning for Open Interest in the 90th percentile, certain industries did appear to be more profitable than others (see Table 7). As expected, industries with higher *CIVD* and *PIVD* values tended to be more profitable. The IT and Telecom industries had more observations fall into the 90th percentile Open Interest than other industries (~25% vs. ~5-10%). For a list of companies in the 90th percentile Open Interest and 90th percentile CIV Inflation, see Table 9.

It should be noted that none of the mean P&L statistics (positive or negative) were statistically significantly different from 0 at the 95% level.

4. Conclusion

Based on our results, it would appear that there is no significant relationship between the size of the EPS estimate range and the change in straddle prices following an earnings announcement. However, Open Interest and CIV Inflation figures do provide incremental information which can be used to identify profitable straddle trade opportunities. These opportunities vary to some extent by year, but certain cutoff

combinations can yield highly profitable returns. Areas for further research would be to use prior year Open Interest and CIV Inflation cutoffs to segregate data, as well as looking more specifically at transaction costs not accounted for in this research.

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Appendix 1: GICS Codes

<u>GICS Code</u>	<u>Industry</u>
10 1010	Energy Energy
15 1510	Materials Materials
20 2010 2020 2030	Industrials Capital Goods Commercial Services & Supplies Transportation
25 2510 2520 2530 2540 2550	Consumer Discretionary Automobiles & Components Consumer Durables & Apparel Hotels Restaurants & Leisure Media Retailing
30 3010 3020 3030	Consumer Staples Food & Staples Retailing Food Beverage & Tobacco Household & Personal Products
35 3510 3520	Health Care Health Care Equipment & Services Pharmaceuticals & Biotechnology
40 4010 4020 4030 4040	Financials Banks Diversified Financials Insurance Real Estate
45 4510 4520 4530	Information Technology Software & Services Technology Hardware & Equipment Semiconductors & Semiconductor Equipment
50 5010	Telecommunication Services Telecommunication Services
55 5510	Utilities Utilities

Table 1: Aggregate Mean and Standard Deviation Statistics

ALL	ACV	EVPR	CIVD	PIVD	CIV Inflation
MEAN	0.128	0.001	-3.51%	-3.46%	1.47%
STD	1.111	0.003	0.056	0.057	0.050
N	8038	8039	8039	8039	8037

ALL	w/ Bid-Offer			w/o Bid-Offer	
	Straddle P&L	Straddle P&L %	Hedged P&L	Straddle P&L	Straddle P&L %
MEAN	(\$0.28)	-11.7%	(\$0.30)	\$0.01	0.5%
STD	0.892	0.287	0.796	0.888	0.268
N	8039	8038	8039	8039	8038

ALL	Bid-Offer	Reverse	Straddle Delta	Absolute Value
		Straddle P&L		Straddle Delta
MEAN	\$0.29	(\$0.30)	0.012	0.252
STD	0.200	0.875	0.313	0.185
N	8039	8039	8039	8039

Table 2: Correlation Matrix

ALL	Reverse										
	Straddle P&L	Straddle P&L %	Bid-Offer	Hedged P&L	Straddle P&L	Open Interest	CIVD	PIVD	CIV Inflation	ACV	EVPR
Straddle P&L	1.000	0.819	-0.129	0.879	-0.933	0.126	-0.400	-0.431	0.035	0.003	0.020
Straddle P&L %		1.000	-0.158	0.676	-0.739	0.170	-0.464	-0.500	0.087	-0.006	0.004
Bid-Offer			1.000	-0.146	-0.207	-0.224	0.041	0.003	0.033	-0.031	-0.045
Hedged P&L				1.000	-0.808	0.139	-0.385	-0.404	0.043	-0.001	0.021
Reverse Straddle P&L					1.000	-0.022	0.363	0.401	-0.044	0.009	-0.001
Open Interest						1.000	-0.223	-0.234	0.004	0.010	0.025
CIVD							1.000	0.741	-0.317	-0.009	-0.015
PIVD								1.000	-0.196	-0.006	-0.011
CIV Inflation									1.000	0.009	0.055
ACV										1.000	0.178
EVPR											1.000

Table 3: Regressions

Straddle P&L (\$):

	Constant	Open Int	CIV Infl	EVPR	Bid-Offer	Y2003	Y2004	Y2005	Y2006	Y2007	R²
<i>Coef</i>	-0.310	0.000	0.793	3.457	-0.475	0.096	0.096	0.072	0.142	0.279	3.4%
<i>t-stat</i>	(-9.84)	(8.26)	(3.99)	(1.05)	(-9.42)	(2.73)	(2.79)	(2.07)	(4.09)	(6.71)	

	Constant	Open Int	CIV Infl	ACV	Bid-Offer	Y2003	Y2004	Y2005	Y2006	Y2007	R²
<i>Coef</i>	-0.306	0.000	0.806	0.000	-0.477	0.097	0.097	0.072	0.143	0.279	3.4%
<i>t-stat</i>	(-9.78)	(8.28)	(4.06)	(-0.00)	(-9.46)	(2.77)	(2.81)	(2.09)	(4.11)	(6.71)	

Straddle P&L (%):

	Intercept	Open Int	CIV Infl	EVPR	Bid-Offer	Y2003	Y2004	Y2005	Y2006	Y2007	R²
<i>Coef</i>	-0.101	0.000	0.548	-0.885	-0.186	0.001	0.003	-0.002	0.023	0.063	5.7%
<i>t-stat</i>	(-10.12)	(11.98)	(8.66)	(-0.85)	(-11.56)	(0.10)	(0.25)	(-0.14)	(2.04)	(4.73)	

	Intercept	Open Int	CIV Infl	ACV	Bid-Offer	Y2003	Y2004	Y2005	Y2006	Y2007	R²
<i>Coef</i>	-0.102	0.000	0.546	-0.003	-0.185	0.001	0.003	-0.002	0.022	0.063	5.7%
<i>t-stat</i>	(-10.25)	(11.98)	(8.64)	(-0.97)	(-11.55)	(0.09)	(0.24)	(-0.14)	(2.03)	(4.73)	

Table 4: Conditional Mean Statistics

ACV Percentile:

Percentile	N	w/ Bid-Offer			w/o Bid-Offer		CIVD	PIVD
		Straddle P&L	Straddle P&L %	Hedged P&L	Straddle P&L	Straddle P&L %		
All	8039	(\$0.28)	-11.7%	(\$0.30)	\$0.01	0.5%	-3.5%	-3.5%
25%	6030	(\$0.26)	-11.3%	(\$0.28)	\$0.02	1.0%	-3.7%	-3.7%
50%	4021	(\$0.26)	-11.1%	(\$0.28)	\$0.02	1.3%	-4.0%	-3.8%
75%	2010	(\$0.24)	-10.1%	(\$0.27)	\$0.02	2.3%	-4.1%	-4.0%
90%	806	(\$0.21)	-10.0%	(\$0.24)	\$0.04	3.3%	-4.5%	-4.3%
95%	404	(\$0.20)	-10.2%	(\$0.23)	\$0.04	3.6%	-4.6%	-4.2%

EVPR Percentile:

Percentile	N	w/ Bid-Offer			w/o Bid-Offer		CIVD	PIVD
		Straddle P&L	Straddle P&L %	Hedged P&L	Straddle P&L	Straddle P&L %		
All	8039	(\$0.28)	-11.7%	(\$0.30)	\$0.01	0.5%	-3.5%	-3.5%
25%	6030	(\$0.27)	-11.6%	(\$0.29)	\$0.01	1.1%	-3.6%	-3.5%
50%	4020	(\$0.25)	-11.1%	(\$0.27)	\$0.03	1.8%	-3.7%	-3.6%
75%	2011	(\$0.23)	-11.0%	(\$0.26)	\$0.04	2.1%	-3.5%	-3.4%
90%	805	(\$0.19)	-10.1%	(\$0.22)	\$0.07	3.6%	-3.8%	-3.6%
95%	403	(\$0.25)	-12.1%	(\$0.25)	\$0.00	1.9%	-3.6%	-3.5%

Open Interest Percentile:

Percentile	N	w/ Bid-Offer			w/o Bid-Offer		CIVD	PIVD
		Straddle P&L	Straddle P&L %	Hedged P&L	Straddle P&L	Straddle P&L %		
All	8039	(\$0.28)	-11.7%	(\$0.30)	\$0.01	0.5%	-3.5%	-3.5%
25%	6030	(\$0.21)	-8.4%	(\$0.23)	\$0.05	1.8%	-4.2%	-4.2%
50%	4020	(\$0.14)	-5.4%	(\$0.16)	\$0.09	3.7%	-5.0%	-4.9%
75%	2011	(\$0.10)	-3.5%	(\$0.11)	\$0.11	4.8%	-5.6%	-5.7%
90%	805	(\$0.01)	-1.1%	(\$0.03)	\$0.17	7.3%	-6.1%	-6.4%
95%	403	\$0.05	1.5%	\$0.00	\$0.21	9.9%	-6.8%	-7.0%
99%	81	\$0.14	7.0%	\$0.11	\$0.27	15.2%	-9.0%	-8.7%

CIV Inflation Percentile:

Percentile	N	w/ Bid-Offer			w/o Bid-Offer		CIVD	PIVD
		Straddle P&L	Straddle P&L %	Hedged P&L	Straddle P&L	Straddle P&L %		
All	8039	(\$0.28)	-11.7%	(\$0.30)	\$0.01	0.5%	-3.5%	-3.5%
25%	6030	(\$0.28)	-10.9%	(\$0.29)	\$0.01	0.9%	-3.9%	-3.6%
50%	4019	(\$0.25)	-9.3%	(\$0.27)	\$0.04	1.9%	-4.9%	-4.3%
75%	2011	(\$0.20)	-6.6%	(\$0.22)	\$0.09	4.1%	-6.5%	-5.7%
90%	805	(\$0.17)	-4.9%	(\$0.18)	\$0.14	5.5%	-8.1%	-7.0%
95%	403	(\$0.19)	-5.4%	(\$0.18)	\$0.13	5.3%	-9.0%	-7.7%
99%	81	(\$0.41)	-9.4%	(\$0.39)	\$0.03	4.7%	-10.2%	-8.2%

Table 4: Conditional Mean Statistics (continued)

Open Interest 90th Percentile AND CIV Inflation Percentile:

Percentile	N	w/ Bid-Offer			w/o Bid-Offer		CIVD	PIVD
		Straddle P&L	Straddle P&L %	Hedged P&L	Straddle P&L	Straddle P&L %		
All	805	(\$0.01)	-1.1%	(\$0.03)	\$0.17	7.3%	-6.1%	-6.4%
75%	231	\$0.08	3.5%	\$0.04	\$0.25	11.2%	-9.5%	-8.7%
90%	76	\$0.17	5.2%	\$0.18	\$0.35	12.4%	-11.9%	-10.5%
95%	41	\$0.16	4.7%	\$0.19	\$0.33	11.7%	-12.8%	-11.8%

Open Interest 95th Percentile AND CIV Inflation Percentile:

Percentile	N	w/ Bid-Offer			w/o Bid-Offer		CIVD	PIVD
		Straddle P&L	Straddle P&L %	Hedged P&L	Straddle P&L	Straddle P&L %		
All	403	\$0.05	1.5%	\$0.00	\$0.21	9.9%	-6.8%	-7.0%
75%	119	\$0.14	6.2%	\$0.05	\$0.28	13.8%	-10.3%	-9.3%
90%	37	\$0.17	7.3%	\$0.13	\$0.33	14.1%	-12.6%	-10.4%
95%	17	\$0.23	9.6%	\$0.19	\$0.39	16.7%	-13.2%	-10.5%

Table 5: Conditional Mean Hit-rate

Open Interest 90th Percentile AND CIV Inflation 90th Percentile:

<u>P&L</u>	<u>N</u>	Frequency	Avg. Straddle P&L	
			\$	%
Positive	50	65.8%	\$0.49	17.4%
Zero	3	3.9%	\$0.00	0.0%
Negative	23	30.3%	(\$0.48)	-20.6%

Open Interest 90th Percentile AND CIV Inflation 95th Percentile:

<u>P&L</u>	<u>N</u>	Frequency	Avg. Straddle P&L	
			\$	%
Positive	37	60.7%	\$0.54	20.2%
Zero	3	4.9%	\$0.00	0.0%
Negative	21	34.4%	(\$0.51)	-21.3%

Open Interest 95th Percentile AND CIV Inflation 90th Percentile:

<u>P&L</u>	<u>N</u>	Frequency	Avg. Straddle P&L	
			\$	%
Positive	24	64.9%	\$0.47	20.2%
Zero	2	5.4%	\$0.00	0.0%
Negative	11	29.7%	(\$0.44)	-19.5%

Open Interest 95th Percentile AND CIV Inflation 95th Percentile:

<u>P&L</u>	<u>N</u>	Frequency	Avg. Straddle P&L	
			\$	%
Positive	12	70.6%	\$0.45	20.1%
Zero	0	0.0%	\$0.00	0.0%
Negative	5	29.4%	(\$0.30)	-15.6%

Table 6: Conditional Mean Statistics By Year

Year	N	w/ Bid-Offer			w/o Bid-Offer		CIVD	PIVD	Open Interest
		Straddle P&L	Straddle P&L %	Hedged P&L	Straddle P&L	Straddle P&L %			
2002	1109	(\$0.40)	-12.9%	(\$0.38)	(\$0.10)	-3.0%	-2.7%	-2.6%	4,813
2003	1497	(\$0.30)	-13.4%	(\$0.32)	(\$0.02)	-0.6%	-2.8%	-2.9%	5,633
2004	1560	(\$0.29)	-12.3%	(\$0.30)	(\$0.01)	0.3%	-3.1%	-3.1%	6,814
2005	1573	(\$0.32)	-13.2%	(\$0.33)	(\$0.01)	0.7%	-3.7%	-3.6%	8,234
2006	1538	(\$0.24)	-10.3%	(\$0.28)	\$0.06	1.7%	-4.4%	-4.3%	8,707
2007	762	(\$0.09)	-5.6%	(\$0.14)	\$0.18	5.4%	-4.7%	-4.7%	10,487

Open Interest 90th Percentile AND CIV Inflation 90th Percentile:

Year	N	w/ Bid-Offer			w/o Bid-Offer		CIVD	PIVD	Absolute Value Straddle Delta
		Straddle P&L	Straddle P&L %	Hedged P&L	Straddle P&L	Straddle P&L %			
2002	17	\$0.03	-1.7%	\$0.19	\$0.19	3.6%	-12.3%	-11.7%	0.15
2003	12	(\$0.03)	0.7%	\$0.05	\$0.08	6.8%	-12.3%	-10.6%	0.24
2004	13	\$0.35	14.1%	\$0.30	\$0.53	20.9%	-12.8%	-12.1%	0.23
2005	14	\$0.07	-3.5%	\$0.08	\$0.27	6.6%	-10.1%	-7.3%	0.21
2006	16	\$0.38	13.1%	\$0.23	\$0.61	21.4%	-11.8%	-10.3%	0.21
2007	4	\$0.37	17.3%	\$0.33	\$0.58	23.3%	-12.7%	-12.8%	0.16

Open Interest 95th Percentile AND CIV Inflation 90th Percentile:

Year	N	w/ Bid-Offer			w/o Bid-Offer		CIVD	PIVD	Absolute Value Straddle Delta
		Straddle P&L	Straddle P&L %	Hedged P&L	Straddle P&L	Straddle P&L %			
2002	5	\$0.26	7.3%	\$0.21	\$0.42	13.2%	-18.6%	-13.3%	0.06
2003	5	(\$0.21)	-0.3%	(\$0.08)	(\$0.11)	6.4%	-11.0%	-10.8%	0.26
2004	6	\$0.33	15.4%	\$0.18	\$0.53	22.1%	-13.4%	-12.2%	0.23
2005	7	(\$0.26)	-13.8%	(\$0.08)	(\$0.13)	-5.4%	-7.7%	-3.6%	0.26
2006	12	\$0.43	16.0%	\$0.25	\$0.60	22.8%	-12.9%	-11.2%	0.21
2007	2	\$0.45	23.2%	\$0.39	\$0.54	26.9%	-14.5%	-15.8%	0.18

Table 7: Conditional Mean Statistics By Industry

Open Interest 90th Percentile:

Industry	N	w/ Bid-Offer			w/o Bid-Offer		CIVD	PIVD
		Straddle P&L	Straddle P&L %	Hedged P&L	Straddle P&L	Straddle P&L %		
Energy	71	(\$0.05)	-2.0%	(\$0.02)	\$0.14	5.9%	-3.6%	-3.0%
Materials	29	\$0.06	2.9%	(\$0.02)	\$0.25	10.7%	-6.0%	-6.1%
Industrials	45	(\$0.08)	0.5%	(\$0.23)	\$0.07	8.1%	-5.9%	-6.1%
Consumer Discretionary	78	(\$0.16)	-6.9%	(\$0.14)	\$0.05	5.3%	-6.3%	-6.6%
Consumer Staples	77	(\$0.19)	-7.7%	(\$0.11)	(\$0.03)	-0.4%	-2.9%	-2.7%
Health Care	90	(\$0.07)	-3.7%	(\$0.12)	\$0.13	6.2%	-3.7%	-4.2%
Financials	102	(\$0.03)	-0.5%	(\$0.03)	\$0.19	6.6%	-2.4%	-2.6%
IT	279	\$0.12	3.0%	\$0.09	\$0.29	10.5%	-10.0%	-10.8%
Telecom	33	(\$0.04)	-5.1%	(\$0.05)	\$0.13	7.3%	-4.0%	-3.2%
Utilities	1	\$0.15	13.0%	(\$0.17)	\$0.30	26.1%	-16.2%	4.4%

Table 8: Percentile Cutoff Values

Percentile	Open Interest	CIV Inflation
25%	698	-0.97%
50%	2,680	0.93%
75%	7,801	3.33%
90%	18,629	6.50%
95%	29,550	9.19%
99%	66,300	16.84%

Figure 1: Conditional Mean Statistics By Year

