The Price Impact of Large Hedging Trades*

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1 Introduction

Financial institutions that issue structured equity products (SEPs) based on individual U.S. common stocks hedge their liabilities by trading in the underlying common stocks. This paper provides direct evidence that the issuers' hedging activity has economically significant impacts on the prices of the underlying stocks, which typically have large capitalizations and high liquidity. In our sample of SEPs, the issuers' hedging trades raise the prices of the underlying common stocks by an average of almost 100 basis points on the pricing dates of the SEPs, with most of the price impact concentrated in the last 30 minutes prior to the close of trading. For one kind of SEP that typically references common stocks with market capitalizations falling in the largest NYSE decile, the price impact on the pricing date averages 143 basis points. A 100 or 140 basis point impact on the price of a stock with a market capitalization in the largest NYSE decile is clearly economically significant. Thus, these results provide direct evidence that hedging of derivatives trades has important, economically significant impacts on the prices of even the very largest and most liquid U.S. common stocks.

Whether, and the extent to which, the trading of equity derivatives impacts the prices of the individual common stocks has long been of interest. Investors, exchange officials, and regulators have been concerned that listed options trading might impact underlying stock prices ever since individual equity options began trading in 1973.[1] However, there is only limited evidence that the trading of equity derivatives on individual equities impacts the prices of underlying stocks, despite a substantial effort to identify the possible impact of such trading.[2] For example, Mayhew and Mihov (2005) find that the apparent effects of option introductions on the price levels of underlying common stocks found in earlier papers disappear when the price level changes are benchmarked against the price changes of matched firms that do not have options introduced. Somewhat similarly, Lamoureux and Panikkath (1994), Freund, McCann, and Webb (1994), and Bollen (1998) demonstrate that the apparent decrease in underlying stock volatility caused by option introduction reported in earlier papers likely stems from the conjunction of the facts that stock volatility is mean-reverting and options exchanges tend to introduce options following increases in volatility. In particular, these researchers find that the decrease in underlying stock volatility

[1] Whaley (2003) contains an account of the early history of exchange-traded options.

[2] This literature is surveyed in Pearson, Poteshman, and White (2008). A separate strand of literature examines the impact of futures trading on the volatility of underlying stock indices (e.g., Bessembinger and Seguin (1992) and Gulen and Mayhew (2000)), especially at index expiration (e.g., Barclay, Henderschott, and Jones (2006) and the references therein). Researchers have also studied the possible impact of mortgage hedging and OTC derivatives dealers' hedging on interest rates (Perli and Sack (2003), Chang, McManus, and Ramagopal (2005), Kambhu (1998), and Kambhu and Mosser (2004)).

following the beginning of option trading also occurs in samples of matched control stocks on which the exchanges do not introduce options.

We are aware of only two studies that provide convincing evidence that the trading of derivatives based on individual common stocks influences the prices of the underlying stocks. Ni, Pearson, and Poteshman (2005) document that option market makers' rebalancing of delta hedges due to the rapid changes in option deltas as the time to expiration goes to zero causes stock prices to "pin" or cluster at option strike prices on option expiration dates,[3] while Pearson, Poteshman, and White (2008) find that option market makers' rebalancing of delta hedges due to changes in stock prices affects the volatilities of the underlying stock prices. This existing evidence is indirect in the sense that these researchers do not observe the order imbalances due to hedge trading, and thus are not able to associate the order imbalances with the underlying stock price movements. In addition, Ni, Pearson, and Poteshman (2005) and Pearson, Poteshman, and White (2008) study only the impacts of hedge rebalancing, not the impacts of the initial hedge trades that market makers enter into when new options positions are established. Initial hedge trades are typical larger than the trades required to rebalance existing hedges, and thus seem likely to have larger impacts on the prices of the underlying stocks. However, it is difficult to study the impact of the initial hedge trades using exchange-traded options because it is difficult to disentangle the price impact of the hedge trade from the price impact of the information contained in the fact that an option or options on the underlying stock just traded. The present paper using a sample of SEPs overcomes this difficulty because, as explained below, the fact that a SEP is being sold to retail investors conveys little or no information about the fundamentals of the company whose stock serves as the reference asset.

This paper uses a a sample consisting of SPARQS, a particular SEP issued by Morgan Stanley, and STRIDES, a similar product issued by Merrill Lynch (now Bank of America Merrill Lynch). These varieties of SEPs are publicly offered, and sold to retail investors. Publicly offered SEPs provide a convenient laboratory to study the impact of derivatives hedging for several reasons. First, because SEPs are liabilities of the issuing financial institution (which hedges its exposure) and are not liabilities of the company whose stock serves as the reference asset, the issue does not convey information held by senior management of the company whose stock serves as the reference asset. In addition, the offering documents describing the SEPs are freely available. Among other things, the offering documents provide the pricing date, and indicate that the SEPs were priced at

[3]The time derivative of the option delta can be very large for a near-the-money option with a short time to expiration, as the absolute value of the delta must go from approximately 0.5 to either 1 or 0, depending on whether the option expires in- or out-of-the-money.

the close of regular trading in the underlying stocks. Because the issuing financial institutions hedge the SEPs close to when they are priced, the approximate time when the issuer places the hedge trades is therefore known, and the hedging trades are apparent in signed order flow estimated from the Trades and Quotes (TAQ) database available from the New York Stock Exchange (NYSE). The quantities of the underlying common stocks that must be traded can be estimated using valuation models for the SEPs, and the observed cumulative order imbalances are consistent with the quantities of trades needed to hedge the SEPs.[4]

Most publicly offered SEPs share the properties of not conveying information about the underlying stock price and having publicly available pricing dates and times. The SEPs in the sample, SPARQS and STRIDES, are particularly convenient because there were large numbers of consistently structured issues, making them well-suited for a broad analysis. Second, they are are relatively short-term: the SPARQS have mean (median) times to maturity and first call of 404 (385) and 213 (201) days, respectively, while the corresponding statistics for the STRIDES are 640 (731) and 318 (367) days. These relatively short times to maturity and call imply that useful implied volatility information is available from the prices of traded options, allowing for the development of accurate valuation models. Some of the analysis requires valuation models to estimate the magnitudes of the stock positions needed to hedge the SEPs.

The pricing date price impacts we document are correlated with the magnitudes of the required hedging trades, and the intraday pattern of price impacts on the pricing date is closely related to the intraday pattern of signed order flow. In addition, the observed price impacts are mostly, but not fully, reversed on the subsequent trading day. This reversal is strong evidence that the price movements we observe are due to the hedging trades rather than to any information conveyed by the SEPs issues. In addition, the paper provides other evidence that helps to rule out the hypothesis that the SEP issues convey information to the market.

Because we know both the magnitude of the hedging trades and the resulting price movements attributable to them, these results provide new estimates of the impact of trading volume on the prices of large-capitalization U.S. common stocks. We also go on to explore the extent to which various measures of (il)liquidity that have been proposed in the market microstructure literature help explain the price impacts. Specifically, we consider covariates formed by interacting the relative size of the SEP issue, defined as the ratio of the total proceeds of the issue to the market capitalization of the underlying stock as of the close of trading on the day before the price date,

[4]This analysis of the relation between the magnitude of the required hedge trades and the cumulative order imbalances has not been completed and is not included in this version of the paper.

with some of the measures of market (il)liquidity studied in Hasbrouck (2006). The results show that the interaction of the relative size with the coefficient estimate in the latent common factor model described in subsection 3.b of Hasbrouck (2006) and the interaction of the relative size with the standard deviation of the returns on the underlying stock are significantly related to the pricing date price impact.

The next section of the paper describes the SEPs used in the sample and the data sources. Section 3 contains the main results regarding the price impact, while Section 4 presents evidence to rule out the hypothesis that the pricing date price impact is due to information conveyed to the market by the SEP issues. Section 5 explores the extent to which various measures of (il)liquidity that have been proposed in the literature can help explain the price impact. Section 6 briefly concludes.

2 Sample and Data

The sample consists of issues SPARQS and STRIDES, particular varieties of SEPs issued by Morgan Stanley and Merrill Lynch (now Bank of America Merrill Lynch), respectively. SEPs are equity-linked notes issued by an investment bank or investment banking subsidiary of a commercial bank, and have payments based on the stock price of another company, a stock index, or multiple stock prices or stock indexes. The SPARQS and STRIDES are based on individual common stocks (or American Depositary Receipts), with the exception of two STRIDES based on stock indexes that we do not include in our analysis. SEPs are marketed primarily to retail customers, as noted by Pratt (1995) and Bethel and Ferrel (2007).[5] Frequently, the issuing financial institution arranges for the SEP to be listed on the American Stock Exchange (AMEX), NASDAQ, or the New York Stock Exchange (NYSE) following issuance, providing at least some secondary market liquidity to the investors. It is worth emphasizing that SEPs are liabilities of the issuing financial institutions, not the companies whose stocks serve as the reference assets.

SEPs are issued based on the issuers' "shelf" registration statements, and are described in pricing supplements to the prospectus. Each pricing supplement contains the terms of a SEP, e.g. the maturity, coupon rate, call provisions, and the exchange ratio, multiplier, or other provision that determines the number of shares of the underlying common (or equivalent cash payment) received by the investor, and also indicates the pricing date (and time, e.g. the close of trading)

[5] We thank Gang Hu for verifying that the SPARQS almost never appear in the extensive dataset of institutional trades used in Hu (forthcoming).

when the issue is priced and sold to investors. All of the issues in our sample were priced as of the close of trading in the underlying stock on the pricing date. When a financial institution believes that there is demand for a SEP based on a particular common stock or stock index it can quickly structure, market, and price a SEP. The SEPs are then sold to investors at about the time or shortly after they are priced, and actually issued about a week later. The issuing firm hedges its liability on the SEP by buying shares of the underlying stock near the time when the SEPs are priced. SEPS that are listed on exchanges typically begin secondary market trading on the next trading day, the first trading day after the pricing date. The issuers file the pricing supplements describing the SEPs with the U.S. Securities and Exchange Commission (SEC), which makes them available through its EDGAR database.[6]

The Morgan Stanley SPARQS included in the sample are the most common of the publicly offered SEP's based on individual equities. From the first SPARQS issue in June of 2001 through June 2009, Morgan Stanley issued 123 SPARQS, with total proceeds of $3,162,820,380. An example of a typical SPARQS is the issue based on National Semiconductor that was priced and sold on April 23, 2004 and issued on April 30, 2004. These securities had a maturity of May 15, 2005, slightly more than one year after the issue date, a coupon rate of 10% per year, a face value and issue price of $23.105, equal to one-half of the April 23 closing price of National Semiconductor. Morgan Stanley could call these SPARQS at any time between October 30, 2004 and May 5, 2005, at an increasing schedule of call prices chosen so that if Morgan Stanley called the SPARQS the payments received by the investor, including the past interest payment already received, would provide an internal rate of return or "yield to call" of 20.5% per year. If Morgan Stanley did not call the SPARQS, on the maturity date of May 15, 2005 the investor would receive at Morgan Stanley's option either one-half share of National Semiconductor or a cash payment equal to one-half of the National Semiconductor closing share price on May 5, 2005. Because the call feature limits the possible payoffs, a SPARQS is similar to a covered call position in one-half share National Semiconductor, where the high coupon of 10% per year is the mechanism through which the investor receives the call premium. A difference between a SPARQS and an ordinary covered call position is that the SPARQS' call price increases over time, creating an incentive for Morgan Stanley to call the SPARQS early even though National Semiconductor did not pay dividends. Exchange ratios of one and one-fourth were also commonly used, so a SPARQS would typically roughly correspond to a covered-call position in one, one-half, or one-quarter share of the underlying common stock.

[6] The SEC's EDGAR database is accessible at http://www.sec.gov/edgar.shtml. The pricing supplements are usually Form 424B3, but sometimes Form 424B2.

Merrill Lynch's STRIDES were similar, in that they also offered a high coupon, were callable at an increasing schedule of call prices, and roughly corresponded to covered call positions in some number of shares of the underlying stocks. An important difference is that the STRIDES most often had original times to maturity of approximately two years rather than one and were first callable after about one year rather than after about six months. Other differences include the facts that many of the STRIDES were structured to have a principal amount of $25 rather than a fraction of the stock price, the final payments of the STRIDES were described in terms of a share multiplier based on the value-weighted average price on the pricing date, and the details of the determination of the final settlement differed. From the first issue in July of 1998 through September of 2008, Merrill Lynch issued 51 different STRIDES, with total proceeds of $2,487,704,000. Two of these issues were based on stock indices rather individual equities, and are not included in our sample. Thus, our sample includes 49 STRIDES, with total proceeds of $2,403,704,000. Combining these with the SPARQS, the total sample consists of 172 issues with total proceeds of $5,566,524,380.

We identify the sample SPARQS and STRIDES by searching the EDGAR database for their pricing supplements and obtain the pricing dates from the pricing supplements. The daily returns and other stock price data such as closing prices and shares outstanding that we use are from the daily price files maintained by the Center for Research in Securities Prices (CRSP). We use trade and quote data in the Trades and Quotes (TAQ) database available from the New York Stock exchange to compute the intraday returns and estimate the intraday signed order volume that we use in some of our analyses. Additionally, factor portfolio returns come from Ken French's website.[7]

Some of the analysis requires valuation models to compute the SEP's deltas as-of the pricing dates. The necessary terms of the instruments are obtained from the pricing supplements. Appropriate implied volatilities of the underlying stocks are from the option prices files from OptionMetrics LLC, while the necessary interest rates (LIBOR for various maturities) are downloaded from Bloomberg. Past ex-dividend dates and dividend amounts used to estimate future dividend dates and amounts are from the CRSP daily file.

Panel A of Table 1 lists the underlying common stocks that were used as the reference stocks for at least three different SPARQS or STRIDES. Apple was the most common underlying stock, with nine SPARQS and two STRIDES issues based on it, followed by Intel and Cisco Systems with six and five issues, respectively, of either SPARQS or STRIDES. The other companies listed in Panel A are mostly large-capitalization technology stocks, along with a few other well-known companies such as Best Buy, Boeing, and Exxon Mobil.

[7]http://mba.tuck.dartmouth.edupagesfacultyken.frenchdata_library.html.

Panel B presents the distribution of the underlying stocks across NYSE market-capitalization quintiles, and also shows the fraction of the underlying stocks falling in the largest-capitalization decile. Each stock is assigned to a size quintile based on cutoffs established by ranking all NYSE stocks by market capitalization at the end of the month immediately preceding the SEP issue. Market capitalization is defined as the product of shares outstanding and the closing stock price.

None of the underlying stocks are in either of the two smallest quintiles, and only 1.16% of the issues, specifically one SPARQS and one STRIDES, had underlying stocks in quintile 3. Slightly more than 86% of the entire sample of underlying stocks were in the largest quintile, with 64.5% in the largest decile. The STRIDES have a more pronounced tendency to be based on large capitalization stocks than does the entire sample. Almost 94% of the STRIDES (46 of the total of 49) were based on stocks in the largest quintile, and 75.5% were based on stocks in the largest decile.

Table 2 provides some summary information about the SPARQS and STRIDES. The median coupon rate was 8% for both varieties of SEP, with mean coupon rates being somewhat greater. As mentioned above, the SPARQS typically had maturities of one year (median = 385 days) versus two years (median = 731 days) for the STRIDES, though the mean times to maturity were somewhat above one year (404 days) and somewhat less than two years (638 days) for the SPARQS and STRIDES, respectively. The yields to call were similar, though slightly higher for the SPARQS, with a median value of 20% versus 17% for the STRIDES. The two kinds of SEPs differed significantly in terms of the issue sizes. The mean and median proceeds for the SPARQS were about $25.7 and $24.2 million, in contrast to mean and median proceeds of $50.4 million and $37.5 million for the STRIDES. However, because the STRIDES tended to be based on underlying stocks with significantly larger market capitalizations, the ratios of the proceeds of the issues to the market capitalizations of the underlying stocks were about the same, with mean (median) values of 0.212% (0.102%) and 0.216% (0.085%) for the SPARQS and STRIDES, respectively.

3 Price Impact of Hedging Trades

Table 3 shows the abnormal performance of the SPARQS' and STRIDES' underlying stocks during eleven-day windows covering the period from five trading days before to five trading days after the pricing dates. The dates shown are in "event time" relative to the pricing dates, i.e. date 0 is the pricing date and date t is the date t days after (or before, if $t < 0$) the pricing date. The first row of results in Panel A shows the average returns of the underlying stocks for the full sample of both SPARQS and STRIDES. The t-statistics for tests of the hypotheses that the average returns are equal to zero are in parentheses below the average returns. The next two rows present the average market-adjusted returns on the underlying stocks and the associated t-statistics for tests of the hypotheses that the average market-adjusted returns are equal to zero. The market-adjusted returns are relative to the returns on the CRSP value-weighted index, that is the market-adjusted return for underlying stock i on day t is $r_{i,t} - r_{M,t}$, where $r_{M,t}$ is the return on the CRSP value-weighted index on day t.

For the pricing date the average raw and market-adjusted returns are 101 and 93 basis points, respectively, and significantly different from zero, with t-statistics of 4.83 and 5.09, respectively. The first trading date after the pricing date (event date 1) shows a striking, though not complete, reversal: the average raw and market-adjusted returns are -80 and -75 basis points, with t-statistics of -4.23 and -4.60, respectively. Returns for none of the other dates are significantly different from zero at conventional levels, with the largest t-statistic for the other dates being 1.54.

The next two rows of Panel A present the numbers of market-adjusted returns that are positive and negative on each day in order to confirm that the significant average returns on dates 0 and 1 are a robust result and not driven by a small number of outliers. On the pricing date the ratio of positive to negative market-adjusted returns is 110 to 62, while on the next trade date the ratio reverses to become 58 to 114. The last row of the panel provides the probability that the number of positive market-adjusted returns equals or exceeds the number of positive market-adjusted returns reported in the table under the null hypothesis that the probability of a positive return is one half. Specifically, the probability reported for date t is $\text{Prob}(k \geq x_t) = \sum_{k=x}^{n} \binom{n}{k} p^k (1-p)^{n-k}$, where x_t is the number of positive market-adjusted returns observed on day t, $\binom{n}{k} p^k (1-p)^{n-k}$ is the probability of k positive returns out of a total of n returns, and $p = 0.5$ is the probability of a positive return under the null hypothesis. On the pricing date the probability under the null of 110 or more positive returns is 0.0002, while on date 1 the probability that 58 or more returns are positive is 0.999994. This latter result implies that the probability under the null that 114 or more of the market-adjusted returns are negative is 6×10^{-6}.

Some context for these results is provided by the ratios of the principal amounts of the SEP issues to the market capitalizations of the underlying stocks on the pricing date. The third column from the right of Table 2 reports that the mean ratios of the SEP proceeds (total principal amounts) to the market capitalizations of the underlying stocks as of the close of trading on the day before the pricing date are 0.212% and 0.216% for the SPARQS and STRIDES, respectively, and the median ratios are 0.102% and 0.085%. The results thus indicate that on average a SEP's issue with a total principal amount equal to about 0.1% or 0.2% of the market capitalization of the underlying stock causes the underlying stock temporarily to increase in value by about one percent.

Panels B and C present the corresponding results for subsamples consisting of the SPARQS and the STRIDES, respectively. The results for both subsamples are similar to those for the full sample in that they show significantly positive average raw and market-adjusted returns on the underlying stocks on the pricing date, and significant, though not complete, reversals on the next trade date. As with the full sample, these results for the average returns are confirmed by the non-parametric tests based on counts of positive and negative returns shown in the last rows of Panels B and C. A difference between the two subsamples is that on the pricing date the average raw and market-adjusted returns of the SPARQS' underlying stocks are only about one-half as large as those of the STRIDES' underlying stocks—80 versus 161 basis points for the raw returns of the SPARQS versus those of STRIDES, and 72 versus and 143 basis points for the market-adjusted returns. A second difference is that Panel B provides some evidence that the SPARQS have a positive average return on day -1. For this day the SPARQS' average market-adjusted return is 43 basis points, with a t-statistic of 2.18. While the average day -1 raw return of 39 basis points has a t-statistic of only 1.68 and the non-parametric test statistic based on the numbers of positive and negative returns has a p-value of 7.44%, it should be recognized that these are less powerful tests.

There is no immediately obvious explanation for the differences in the pricing date average returns of the two varieties of SEP. Table 2 reveals that the STRIDES issues tend to be larger, with mean and median proceeds of $50.4 and $37.5 million, respectively, in contrast to $25.7 and $20.4 million for the SPARQS. However, the STRIDES' underlying stocks have correspondingly larger market capitalizations, so that the ratios of the proceeds to the market capitalizations of the underlying stocks as of date -1 are similar. As indicated above, the mean ratios are 0.212% and 0.216% for the SPARQS and STRIDES, respectively, and the median ratios are 0.102% and 0.085%. The lack of any immediately apparent explanation, combined with the positive average return of the SPARQS but not the STRIDES on date -1, leads us to conjecture that Morgan Stanley starts to buy stock to hedge the SPARQS on date -1 while Merrill Lynch waits until the pricing date. We explore this conjecture below.[8]

The striking return reversals observed on the day after the pricing date strongly suggest that the price movement on the pricing date is due to the price impact of the issuers' hedging trades in the underlying stocks. Figures 1 and 2 further explore the price impact of the issuers' hedging trades in the underlying stocks by examining intraday returns and net buying volume. For the SPARQS

[8]This analysis has not been completed, and is not included in this version of the paper.

and STRIDES, respectively, the two figures show the average intraday cumulative market-adjusted returns (left scale) and intraday cumulative net buying volume (right scale) for the underlying stocks during 5-minute intervals throughout the pricing date. The market-adjusted returns are computed relative to the return on the S&P Depositary Receipts (SPDRs, ticker symbol SPY). For each 5-minute interval, the return on the underlying stock is computed from (i) the price of a transaction that has a time stamp that falls within the interval and is at or closest to the end of the interval, and (ii) the closing price from the previous day. The SPDRs' returns are computed similarly. Net buying volume is estimated by classifying each trade as either a "buy" or "sell." First, trades that occur at or above (below) the prevailing ask (bid) price are classified as "buy" ("sell") trades.[9] Following the methodology of Lee and Ready (1991), trades inside the quotes are classified according to the tick test where trades are classified "buys" if they occur on an uptick or zero uptick and "sells" if they occur on a downtick or zero downtick.[10] The net buying volume for each 5-minute interval is the sum of the buy and sell orders that have time stamps that fall within the interval, treating a sell as a negative buy, and the cumulative net buying volume is the sum of the net buying volume for the current interval and all previous intervals.

Figure 1 for the SPARQS shows a significant order imbalance during the 5-minute interval that includes the open, with average net buy volume of about 102,000 shares, along with a large average initial return of 29.5 basis points. Following the open, average cumulative net buy volume increases at an approximately constant rate to a level of about 366,000 shares at 3:30 p.m., followed by average net buying volume of more than 220,000 additional shares from 3:30 to the close of trading. After the initial return of 29.5 basis points the cumulative market-adjusted return increases only slightly through most of the day, to 36.5 b.p. at 3:30 p.m., and then increases very rapidly to the close of trading. Thus, average cumulative net buying and market-adjusted returns display similar patterns, with the main difference being that larger proportions of the cumulative return are realized in the 5-minute interval that included the open and after 3:30 p.m.[11]

Figure 2 for the STRIDES differs from Figure 1 in that it does not show a significant imbalance

[9]Following the Lee and Ready (1991) algorithm, we exclude all trades with special settlement conditions, and the prevailing quotes are computed from the most recent eligible quotes five seconds prior to the trade price.

[10]We eliminate all quotes meeting any of the following criteria: negative bid; negative ask; negative depth; negative spread; spreads greater than $5; quote modes that are not NBBO eligible.

[11]The average intraday returns as of 4:05 p.m. in Figures 1 and 2 do not exactly match the average market-adjusted pricing date returns in Panels B and C of Table 3 because the market adjustment in Figures 1 and 2 is done using the return on the S&P Depositary Receipts (SPDRs) while the market adjustment in Table 3 is done using the return on the CRSP value-weighted index. The return on the SPDRs differs from the return on the CRSP value-weighted index both because the SPDRs do not exactly track the reported S&P, and because the S&P differs from the CRSP value-weighted index. In addition, the last exchange traded used to compute the CRSP daily return often has a time stamp after 4:05 p.m., and thus differs from the trade used to compute the return in the last time interval shown in the figures. This latter fact applies to both the underlying stocks and the SPDRs.

of net buys during the 5-minute interval that includes the open; instead, both average net buys and the average market-adjusted return are slightly negative during the first 5-minute interval. After the first 5 minutes, both climb steadily throughout the day, and then very rapidly toward the end of the day. The two lines display strikingly similar patterns; in fact, the lines showing the cumulative net buys and market-adjusted return are so similar that they actually cross each other many times during the day.

4 Might the SEP's issuances convey information to the market?

The results in the previous section are consistent with the hypothesis that the issuers' hedging trades have important impacts on the prices of the underlying stocks. A possible alternative hypothesis that must be ruled out is that the issues convey some positive information about the underlying stocks. While this is a possible hypothesis, *a priori* there is reason to doubt that SEP issues convey positive information to the market. First, we emphasize that the SEPs are liabilities of the issuing financial institutions, not the companies whose stocks serve as the reference assets. Thus, a SEP issue cannot convey private information held by the senior managers of the company whose stock provides the reference asset. Second, to the extent that the issuing financial institution either does not hedge or only partially hedges its exposure to the underlying stock price, it will benefit from decreases in the stock price, and will suffer mark-to-market losses on the combined position of SEP and underlying stock if the stock price increases. Hence, if the issuer does not fully hedge its exposure then the SEP issue should convey negative rather than positive information about the underlying stock. We provide additional support for these arguments by turning to the data.

An important piece of evidence that the SEP issues do not convey information to the market stems from the fact that Morgan Stanley filed preliminary pricing supplements for all of the SPARQS issued (priced) between September 30, 2002 (September 23, 2002) and January 31, 2006 (January 24, 2006), inclusive. These preliminary pricing supplements were filed with the U.S. Securities and Exchange Commission (SEC) between 6 and 29 days before the pricing date, with an average of 20.8 days, and were publicly available through the EDGAR database accessible via the SEC's website.[12] Each identified the SPARQS' underlying stock, and included some, though not all, of the terms of the issue; for example the offering price was unknown as of the filing date of the preliminary pricing supplement and thus could not be included. For this subset of the SPARQS

[12]The mean and minimum number of days are computed excluding the issue for which the filing date of the preliminary pricing supplement is after the pricing date.

issues, the information that an issue was forthcoming was released not on the pricing date but on average 20.8 days earlier. If the SPARQS issues convey positive information about the underlying stocks then there should be a positive price impact on the filing of the preliminary pricing supplement. In addition, for the subset of issues with preliminary pricing supplements there should be minimal price impact on the pricing date, as the only information that comes out on the pricing date is the fact that the SPARQS issue was not canceled between the filing date and the pricing date. Only seven of the 66 preliminary pricing supplements did not result in completed SPARQS issues.

Table 4 presents the average raw and market-adjusted returns of the underlying stocks for this subset of SPARQS for eleven-day windows centered on the filing date of the preliminary pricing supplement (Panels A and B) and the pricing date (Panel C).[13] The cutoff for filing the preliminary pricing supplement is 5:30 p.m. on the filing date, after the close of trading, so one should look for evidence of price impact on both the filing date and date +1. The average raw and market-adjusted returns on the filing date are not significantly different from zero, with point estimates of 49 and 34 basis points, respectively, and t-statistics of 1.56 and 1.35. While the point estimate of 34 basis points for the average market-adjusted return might seem large, note that two of the other ten average market-adjusted returns, those on days +3 and +5, exceed 34 basis points, and three others equal or exceed 29 basis points (those on days −5, −3, and −2). Thus, a point estimate of 34 basis points is not atypical. Turning to the average raw returns, the return of 77 basis points on day +3 exceeds the average return of 49 basis points on the pricing date, and two of the other days (−2 and + 5) have returns greater than or equal to 45 basis points. The non-parametric test based on counts of positive and negative market-adjusted returns has a p-value of 5.44%. The average raw and market-adjusted returns on day +1 are negative, with negative returns slightly outnumbering positive returns.

Henderson and Pearson (2009) find that market-adjusted returns prior to the pricing date help explain SPARQS issues in logistic regressions, while Bergstresser (2008) finds that past returns are significant explanators in ordinary least squares regressions in which the dependent variable is the year-over-year change in either the count or total principal amount of SEPs issues during a month. The filing dates of the preliminary pricing supplements typically fall within the interval covered by the return variables used by Henderson and Pearson (2009), and often fall within the

[13]These results include the returns on the underlying stock for the issue for which the filing date of the preliminary pricing supplement was three days after the pricing date. How to handle this is unclear. In contrast to the vast majority of the other SPARQS, this issue was not listed on the AMEX or any other exchange. Thus, the information that a SPARQS had been issued was not freely available to the public prior to the filing date.

return interval used by Bergstresser (2008). The fact that SEP issues are (positively) related to past market-adjusted returns leads to possible selection biases because the issuer might tend to file preliminary pricing supplements for issues based on underlying stocks that had positive market-adjusted returns through the close of trading on the filing date (recall that the filing cutoff is 5:30 p.m. after the close of trading), or because the issuer might have a tendency to cancel issues based on stocks that suffered negative market-adjusted returns during a period that includes the filing date. This latter selection bias is ameliorated by the fact that we include in Panel A the seven filings that were not followed by SPARQS issues, but can still exist if large technology stocks generally outperformed the CRSP value-weighted index during the period in which Morgan Stanley followed the practice of filing preliminary pricing supplements. Examination of the average returns in Panel A for days -5 through -1 reinforces this concern about possible selection biases. All five of the reported average raw returns, and four of the five average market-adjusted returns, are positive, with the only negative average market-adjusted return being 8 basis points on day -4. Looking at slightly longer periods that are not included in the table, the average raw and market-adjusted returns from event day -10 to -1 are 18.3 and 15.0 basis points, with t-statistics of 1.88 and 1.77, respectively. The average raw and market-adjusted returns from event day -15 to -1 are 19.1 and 15.6 basis points, with t-statistics of 2.36 and 2.23, respectively.

In Panel B we adjust for this possible selection bias by using benchmarks that include the average of the returns over the previous 10 days. Specifically, rather than compute average raw returns $(1/66)\sum_{i=1}^{66} r_{i,t}$ we subtract from each raw return the average, across both underlying stocks and time, of the raw returns over the previous 10 days, and compute $(1/66)\sum_{i=1}^{66}(r_{i,t} - \mu(t-10, t-1)$, where $\mu(t-10, t-1) = (1/660)\sum_{k=1}^{10}\sum_{i=1}^{66} r_{i,t-k}$. For the analyses of market-adjusted returns we subtract from each market-adjusted return the average, across both underlying stocks and time, of the market-adjusted returns over the previous 10 days, and compute $(1/66)\sum_{i=1}^{66}(r_{i,t} - r_{M,t} - m(t-10, t-1)$, where $m(t-10, t-1) = (1/660)\sum_{k=1}^{10}\sum_{i=1}^{66}(r_{i,t-k} - r_{M,t-k})$. This adjustment will not fully correct for the selection bias to the extent that a tendency to file preliminary pricing supplements for issues based on underlying stocks that had positive market-adjusted returns on the filing date itself is important. Regardless, this adjustment for the selection bias reduces the pricing date average raw and market-adjusted returns to 31 and 19 basis points, respectively, with t-statistics of 0.975 and 0.754, respectively. The non-parametric test based on the counts of positive and negative market-adjusted returns has a p-value of 19.45%. Taken together, the results in Panels A and B do not provide significant evidence that the filing of a pricing supplement describing a forthcoming SPARQS issue conveys information to the market.

This is confirmed by Panel C, which presents the average pricing date returns of the set of SPARQS issues for which preliminary pricing supplements were filed. The average pricing date raw and market-adjusted returns are 72 and 60 basis points, respectively, with t-statistics of 2.36 and 2.23, respectively. This finding of significant returns on the pricing date for this subset of issues for which preliminary pricing supplements were filed is inconsistent with the hypothesis that the pricing date returns are due to information conveyed by the issue, because for this set of issues the information was available to the market on average 20.8 days before the pricing date, upon the filing of the preliminary pricing supplement. The average returns for these issues are smaller than the average returns for the entire population of SPARQS issues shown in Panel B of Table 3, which might be at least partly due to to the fact that for this subset the average ratio of the proceeds to the market capitalization of the underlying stock was only 1.64%, less than the ratio of 1.73% for the entire sample. The underlying stocks of these issues also display return reversals on day +1. For this subset the average returns on day +1 are not significantly different from zero, though the non-parametric test based on counts of positive and negative market-adjusted returns is significant, as the reported value of 0.9908 for the probability that 21 or more returns were positive by chance implies that the probability that 38 or more were negative by chance is $0.9908 - 1 = 0.0092$ or 0.92%.

Examination of the abnormal returns to the underlying stocks over long horizons provides additional evidence regarding the information content of the SEPs issues. If the SEPs issues do convey information to the market about the future performance of their underlying stocks, one would expect to find that information validated in the underlying stocks' long-horizon performance. For this reason, we also examine risk-adjusted performance of the full sample of SEPs relative to three benchmarks, the market index, the Fama and French (1992) three-factor model, and the Carhart (1997) four-factor model. In the market model, the return for the underlying stock is

$$r_{i,t} - r_t = \beta_i \left(r_{M,t} - r_t \right) + \varepsilon_{i,t}, \tag{1}$$

where $r_{i,t} - r_t$ is the excess return of the underlying stock i on date t over the risk-free rate of return r_t and $r_{M,t} - r_t$ is the excess return on the value-weighted CRSP market portfolio on date t. In the three-factor model, the return on the underlying stock is

$$r_{i,t} - r_t = \beta_i \left(r_{M,t} - r_t \right) + s_i \left(SMB_t \right) + h_i \left(HML_t \right) + \varepsilon_{i,t}, \tag{2}$$

where SMB_t are the excess returns to the portfolio of small stocks over large stocks on date t, and HML_t are the excess returns to the portfolio of high book-to-market firms over low book-to-market firms.[14] Referring back to Table 1, the reference equities tend to be large growth stocks, and there is reason to believe that the market model may provide an incomplete benchmark for such stocks (e.g., Fama and French (1992)). For this reason, the Fama and French (1992) three-factor model in (2) might be more appropriate. Additionally, since Henderson and Pearson (2009) find that SPARQS tend to be issued following high returns, we consider the return on the underlying stocks in the four-factor model of Carhart (1997) which are

$$r_{i,t} - r_t = \beta_i \left(r_{M,t} - r_t\right) + s_i \left(SMB_t\right) + h_i \left(HML_t\right) + m_i \left(MO_t\right) + \varepsilon_{i,t}, \tag{3}$$

where MO_t is the return to the portfolio of high momentum stocks minus the return to the portfolio of low momentum stocks.

If the underlying stocks outperform the benchmarks, the accumulated (over event-time) averages of the residuals in equations (1), (2), and (3) should be positive. Testing these hypotheses requires both averaging the residuals across underlying stocks and accumulating them over time.[15] Let N be the number of underlying stocks, let τ_i be the calendar-time pricing date of the ith SEP, and let t, and later u, index event time relative to the pricing date, i.e. $t = 0$ is the pricing date, $t = 1$ is the first trading day following the pricing date, etc. With this notation $\tau_i + t$ is the calendar date t days following the pricing date. We are interested in testing the hypothesis:

$$\sum_{t=1}^{L} \left(\frac{1}{N} \sum_{i=1}^{N} \epsilon_{i,\tau_i+t} \right) = 0, \tag{4}$$

where the residuals being summed are defined in equations (1), (2), or (3), depending upon whether the market, three-factor, or four-factor model is being used. Appendix A describes the computation of standard errors for the the cumulative average residual returns (CARRs) on the left-hand side of equation (4).

Table 5 presents the CARRs for the three models for various periods following the issue dates, along with their standard errors, t-statistics, and sample sizes. After the first two days, these CARRs do not exhibit any significant over- or under-performance of the underlying stocks relative to the market index. However, the post-event returns for the first and second days are negative and significant, indicating brief underperformance of the underlying stocks which is consistent with the return reversals on day +1 following the pricing date reported in Table 3.

[14] The time series of factor portfolio returns are made available by Ken French at the website http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html.

[15] For the CARRs analysis, we estimate the factor loadings for each underlying stock from monthly returns over the 60 months preceding the pricing date. We eliminate from the CARRs analysis the 5 observations where the underlying stock did not have at least 30 monthly returns available in CRSP. Additionally, we restrict the analysis to observations with at least six months of daily returns in CRSP following the SEP pricing date. This eliminates from the sample 6 SPARQS issued during 2009, leaving a sample of 162 firms for the CARRs analysis.

Next, Table 5 reports the CARRS in equation (4) based on equation (2), the three-factor model for the underlying stocks. These CARRs also demonstrate that the reference equities experience significantly negative risk-adjusted performance over the first two days following SPARQS issuances. The underperformance dissipates quickly and the results do not demonstrate subsequent abnormal performance of the stocks relative to the three-factor benchmark. Although the differences are not statistically significant, the CARRs for the underlying stocks are lower when the benchmark is the market model than the three-factor model, consistent with the market model over-estimating the required returns to large growth stocks.

Finally, Table 5 reports the CARRs in equation (4) based on equation (3), the four-factor model for the underlying stocks. Since the underlying stocks on average have negligible loadings on the momentum factor, it is not surprising that the CARRs from the four-factor model are qualitatively and quantitatively similar to those of the three-factor model. Again, the CARRs are negative and significant for the two days following the pricing date and thereafter do not exhibit any significant over- or under-performance.

Table 6 completes the examination of the SPARQS' post-issuance performance by presenting the results of regressing the calendar-time returns of portfolios comprised of the reference equities on the returns of benchmark portfolios. The CARR test statistics discussed above address the cross-sectional correlation in the post-issuance returns that are overlapping in calendar time by making specific parametric assumptions about the cross-sectional correlations of the returns on the reference equities. The calendar-time portfolio return regressions supplement the CARR analysis because they handle the cross-sectional correlations due to overlapping return windows without specifying a parametric model of the cross-correlations. In our context the calendar-time approach is preferred to buy-and-hold methodologies (e.g., Lyon, Barber, and Tsai (1999) and Loughran and Ritter (2000)) because the cross-sectional correlations that stem from overlapping return windows are not addressed by typical buy-and-hold methodologies and present a severe problem in our sample, as all of the SEP issues in our sample occur during a period of just less than eight years (see Mitchell and Stafford (2000)).

Each month, the calendar-time portfolio consists of an equally-weighted portfolio of the underlying stocks of the SEPs issued during the preceding six months. The sample used in the calendar-time regressions begins with June 2001 when the first two SPARQS were issued.[16] Employing the

[16]The first sample observation is a STRIDES issued during 1998. We eliminate this from the sample used in the calendar-time regressions because that issue was the only one prior to June 2001, so including it would have meant that for a number of months the equal-weighted portfolio consisted of only a single stock. Starting in June 2001 significant numbers of SEPs began to be issued.

market, three-factor, and four-factor models, the regression equations are

$$r_{\Pi,t} - r_t = \alpha + \beta\,(r_{M,t} - r_t) + \epsilon_t, \tag{5}$$

$$r_{\Pi,t} - r_t = \alpha + \beta\,(r_{M,t} - r_t) + s\,(SMB_t) + h\,(HML_t) + \epsilon_t, \tag{6}$$

$$r_{\Pi,t} - r_t = \alpha + \beta\,(r_{M,t} - r_t) + s\,(SMB_t) + h\,(HML_t) + m\,(MO_t) + \epsilon_t, \tag{7}$$

where $r_{\Pi,t}$ is the return on the equally-weighted portfolio of the stocks underlying SPARQS and STRIDES issued during the previous 200 trading days and all other variables are as defined previously. The null hypothesis that the stocks abnormal returns are zero implies that the intercept $\alpha = 0$. The regression results presented in Table 6, provide no evidence that the underlying stocks experience abnormal performance following a SEP issue, as the estimated intercepts are only 6, 27, and 27 basis points per month, with t-statistics of only 0.114, 0.547, and 0.542, respectively. The loadings of the portfolio returns on the market factor indicate that the SPARQS' and STRIDES' reference stocks on average have a positive, significant loading on the market risk factor, a negligible loading on the size factor, a significant negative loading on the book-to-market factor, and a negligible loading on the momentum factor. These factor loadings are consistent with the summary information about the underlying stocks provided in Table 1.

Taken together, these results are consistent with the assertion that issuance of the SPARQS or STRIDES referenced to a particular stock does not convey information about the underlying stock. The CARRs analysis fails to reject that the underlying stocks have returns equal to the benchmark indexes following the issue date. Consistent with this finding, the small and insignificant intercepts from the calendar time regressions indicate that the portfolios of underlying stocks do not exhibit over- or under-performance following the structure products issue, suggesting the positive stock price reaction on the pricing date is not the result of information regarding the underlying stocks.

5 Is the Price Impact Explained by Measures of Liquidity?

We next explore whether the price impact is explained by measures of stock market liquidity by regressing the pricing date market-adjusted returns on several measures of and proxies for (il)liquidity that have been proposed in the literature. This investigation is motivated by two considerations. First, if one maintains the hypothesis that at least one of the measures or proxies actually captures market liquidity, the results should show that one or more of the right-hand side variables is significantly related to the pricing date market-adjusted return. Failure to obtain such a result would cast doubt on the interpretation of the price impact as being due to the price impact of hedging trades rather than information conveyed by the SEP issue, and thus serves as another test of this hypothesis. Second, the results provide evidence regarding which of the proposed measures of and proxies for liquidity are able to explain the price impact of trading volume.

This investigation considers some of the measures of market liquidity discussed in Hasbrouck (2006), along with a few other variables. The measures discussed in Hasbrouck (2006) that we consider are as follows:

1. The Roll (1984) measure of effective trading costs, estimated as the square root of the negative of the autocovariance of daily log returns, and set to zero when the sample autocovariance is positive.[17] This measure is denoted c^{Roll}.

2. The estimate of the coefficient c^{BMA} in what Hasbrouck calls the basic market-adjusted model[18]
$$\Delta p_{it} = c_i^{\text{BMA}} \Delta q_{it} + \beta_i r_{mt} + u_{it}, \tag{8}$$
where p_t is the log of the price so that $\Delta p_t = p_t - p_{t-1}$ is a log return, $\Delta q_t = q_t - q_{t-1}$, where q_t is a trade direction indicator taking the values $+1$ or -1 for buys and sells, respectively, r_{mt} is the market return, and u_t is a residual independent of Δq_t and r_{mt}. The trade direction indicators q_t are unobserved because the model is estimated from daily CRSP data, and the coefficient estimates are obtained using the Gibbs sampler.

3. The intercept γ_0 and slope coefficient γ_1 from the latent common factor model given by the equations[19]
$$\begin{aligned} c_{it} &= \gamma_{0i} + \gamma_{1i} z_t, && (9) \\ \Delta p_{it} &= (\Delta q_{it})(\gamma_{0i} + \gamma_{1i} z_t) + \beta_i r_{mt} + u_t, && (10) \end{aligned}$$
where z_t is the latent common factor.

We also use the use the return standard deviation σ estimated from the 20 returns from day -20 to day -1. We interact each of the liquidity measures with the relative size of the SEP issue, defined as the ratio of the total principal amount of the SEP issue to the market capitalization of the underlying stock as of the close of trading on the day before the pricing date, multiplied by 1,000. We interact the liquidity measures with the relative size variable because it is clear that the price impact should be increasing in the size of the issue (e.g., the price impact must be zero if the

[17] See Hasbrouck (2006), pp. 6-7, 20.
[18] Hasbrouck (2006), eq. (3) on p. 11.
[19] See Hasbrouck (2006), eqs. (6)–(7) on p. 15.

size is zero), and there is a theoretical argument that the price impact of a trade should be linear in the size of the trade (Kyle (1985), Huberman and Stanzl (2000)). The measures discussed in Hasbrouck (2006) were computed by him through 2006 and made available on his website,[20] and the regressions with liquidity measures use the intersection of our sample with the issues for which the liquidity measures are available.

Table 7 reports the results from estimating specifications that include various subsets of these variables. The first column headed (1) shows results for a specification that includes only the relative size variable, denoted RelSize. As expected, the coefficient estimate on relative size is significantly different from zero (t-statistic 2.917), and large: the point estimate of 0.0025 indicates that one percentage point increase in the ratio of the SEP proceeds to the market capitalization of the underlying stock increases the price impact by 0.025 or 250 basis points. The next four columns headed (2) through (5) each include RelSize along with a variable formed by interacting one of the liquidity measures with RelSize, except that the coefficients γ_0 and γ_1 from the latent common factor model are included together in the specification reported in column (3). The results reported in columns (3) and (5) indicate that the variables $\gamma_1 \times$ RelSize and $\sigma \times$ RelSize are significantly related to the price impact, with t-statistics of 3.958 and 3.642, respectively. In both of these regressions the coefficient on RelSize either becomes small and insignificant (column (3)) or negative (column (5)), indicating that the size of the issue matters only through its interaction with the (il)liquidity variables. In column (2) the coefficient c_{BMA} in the basic market-adjusted model is less strongly related to the price impact (t-statistic 1.614), though including this variable in the regression also eliminates the impact of RelSize. The results in column (4) provide no evidence that the Roll (1984) measure of trade costs is related to the price impact.

Column (6) presents the results for a specification that includes all of the liquidity variables, with each still interacted with RelSize. Consistent with the results in columns (2)–(5), both the γ_1 coefficient from the latent common factor model and the return standard deviation σ are significantly related to the price impact, and the other liquidity measures are not. The coefficient on RelSize is small (and actually negative) and insignificant, consistent with the idea that the size of the SEP issue only matters through its interaction with the (il)liquidity measures. The R^2 of 0.31 is comfortingly large given that the cross-sectional average of the underlying stocks' daily return standard deviations is 267 basis points, implying that there is a large residual component to the stocks' returns that cannot plausibly be explained by the right-hand side variables. This finding that some of the liquidity measures explain the price impact, and that RelSize matters only through

[20]See http://pages.stern.nyu.edu/ jhasbrou/Research/GibbsEstimates2006/Liquidity%20estimates%202006.htm

its interaction with the liquidity measures, is consistent with the hypothesis that the pricing date price impacts are caused by the hedging trades and not by any information conveyed by the SEP issues. The alternative hypothesis that the price impacts are caused by information conveyed by the SEP issues does not predict that the price impact will be related to the liquidity measures and suggests an independent role for the size of the issue, exactly the opposite of what is found. The only possibly anomalous result in this specification is the relatively large (44 basis point) point estimate of the intercept, though this estimate is not significantly different from zero (t-statistic of 1.320).

The final specification reported in column (7) addresses the finding in Table 3 that the price impact of the STRIDES issues is much larger than that of the SPARQS issues. As noted in Section 3, there is no immediately obvious explanation for this. Although the STRIDES issues tend to be larger than the SPARQS, their underlying stocks are also larger, and the means of their relative sizes (total principal to market capitalization of the underlying stock) are almost identical (and the median relative size of the STRIDES is actually smaller than the corresponding median for the SPARQS). The final specification in column (7) addresses this by including a dummy variable "STRIDES" that takes the value 1 for a STRIDES issue and 0 for a SPARQS issue, along with an interaction term formed from the product of this dummy variable and RelSize. Comparing the results in columns (6) and (7), the coefficient estimates on RelSize and the variables constructed by interacting the liquidity measures with RelSize are little changed, so none of the previous conclusions are affected. The point estimate on the STRIDES dummy variable is insignificant (t-statistic 1.305), and the estimate on the interaction term STRIDES $\times$ RelSize is both small and insignificant. Interestingly, the point estimate on the STRIDES dummy variable is 85 basis points, close to the average difference between the price impact of the STRIDES and the SPARQS, and the inclusion of the STRIDES dummy variable and the interaction term formed from it reduces the point estimate on the intercept from 44 to 11 basis points. This is intriguing preliminary result that suggests that it might be useful to try and increase the sample size and explore further differences between the price impact of STRIDES and SPARQS issues.[21]

[21] The sample used in these current regressions consists of the intersection of the sample of SPARQS and STRIDES and the Hasbrouck (2006) data that extends only through 2006.

6 Conclusion

This paper documents that the underlying stocks of a sample of SEP issues experience surprisingly large market-adjusted returns on the SEP's pricing dates. For the SPARQS' underlying stocks the average pricing date market-adjusted return is 93 basis points, while for the STRIDES' underlying stocks the average market-adjusted return is 143 basis points. There is convincing evidence that these returns are due to the price impact of the trades in the underlying stocks that the issuers execute in order to hedge their liabilities on the SEPs. These results demonstrate the existence of an important interaction between the markets for equity derivatives and their underlying stocks, in which stock trades placed in order to hedge derivatives positions have important impacts on the prices of the underlying stocks. The existence and importance of such interactions is a question that has been of long-standing regulatory and policy interest.

These results also have immediate implications for the pricing and valuation of derivatives positions based on individual equity prices, e.g. for the bid-offer spread on an equity swap or other equity derivative. The bid-ask spread must be large enough to compensate the derivatives market maker for the price impact of the trades in the underlying stock necessary to hedge the derivative. The results in this paper provide estimates of the price impact for a sample of large-capitalization underlying stocks.

Related to this, an issue that arises in the specialist risk management function of large financial institutions is how to estimate liquidation values of positions in financial instruments, e.g. what is the relation between the quoted market price and the value that can be realized from the (perhaps forced) liquidation of a large position (See, e.g. Allen (2003)). The discount of the liquidation value to the quoted price is determined by the price impact of the trades needed to liquidate the position, and the results in this paper provide relevant evidence about the magnitude of the price impact for common stock positions.

An important advantage of the results in the current paper relative to some alternative estimates of the price impact of trading volume is that the total number of shares needed to hedge a SEP issue is exogenous to the price impact of those trades, i.e. the return on the pricing date does not affect the number of shares needed to hedge the SEP issue.[22] This is not the case with alternative approaches that involve aggregating signed order flow during say 5 or 30-minute time intervals and

[22]The SEPs in our sample are priced at the close of trading. One result of this is that the SEPs' deltas are not functions of the pricing date returns. It appears that the bulk of the hedging trades are executed prior to the close of trading on the pricing date. To the extent that all are, the number of shares traded is not affected by the pricing date returns. Even if some hedging trades are executed on the next trading day, the total number of shares required to hedge will not be importantly affected by the intra-day returns on the next day because the embedded options in the SEPs are well out-of-the-money on the pricing dates and their gammas are not large.

regressing returns over the same intervals on the estimates of signed order flow. To the extent that either market makers set quotes to manage their inventories, derivatives traders whose positions have non-zero gammas rebalance their hedges, or the market includes some short-term feedback traders, the return over a say 30-minute interval will affect the signed order flow during the interval. Thus, such alternative approaches are potentially affected by an endogeneity bias.

7 Compare to Obizhaeva's Price Impact Estimates

It seems interesting to compare our estimates of price impact to those in Obizhaeva (2009). In that paper the proportional price impact per unit of standard deviation for the ith stock is given by (see Obizhaeva (2009) Equation (1))

$$\frac{dP_{t,i}}{P_{t,i} \times \sigma_{r,i}} = \tilde{\lambda} \times \left(\mathrm{I}_{BS,i} \times \frac{dXt,i}{ADV_i} \right) + d\widetilde{Z}_{t,i}, \tag{11}$$

where $\sigma_{r,i}$ is the standard deviation of daily returns of the ith stock, $\tilde{\lambda}$ is the price impact parameter, $\mathrm{I}_{BS,i}$ is the trade direction indicator taking the value 1 for buy orders and -1 for sell orders, $dX_{t,i}$ is the size of the trade in the ith stock, measured as the number of shares, ADV_i is the average daily volume in the ith stock, also measured in shares, and $d\widetilde{Z}_{t,i}$ models the random arrival of new public information. Note that in equation (11) the trade $dX_{t,i}$ is scaled by average daily volume, so that the right-hand side variable $dX_{t,i}/ADV_i$ is the trade measured as the fraction of shares outstanding. For her overall sample combining buy and sell orders in both NYSE/AMEX and NASDAQ-listed stocks Obizhaeva (2009) estimates $\tilde{\lambda}$ to be 0.30. For the subsamples of buy (sell) orders in the NYSE/AMEX-listed stocks she estimates $\tilde{\lambda}$ to be 0.85 (0.32), while for buy (sell) orders in NASDAQ-listed stocks she estimates the parameter to be 0.85 (0.23).

Perhaps surprisingly, Obizhaeva (2009) finds that the price impact is generally larger for stocks with higher trading volume. (She offers the plausible explanation that buy orders amounting to say 1% of volume are not unusual for a lower-volume stock, but are unusual for a high-volume stock in which there is ordinarily a large flow of both buy and sell orders. Thus, a buy order of 1% of daily volume in a high-volume stock carries more information.) She also finds that for the overall sample the price impact of buys is greater than that of sells. Specifically, she estimates the parameter $\tilde{\lambda}$ from both buys and sells for 10 different groups of stocks, determined by thresholds equal to the 30th, 50th, 60th, 70th, 75th, 80th, 85th, 90th, and 95th percentiles of average daily volume for NYSE-listed common stocks. Her largest group (volume above the 95th percentile) seems to be the one that best matches the underlying stocks of the SPARQS and STRIDES. For this group, the estimates of $\tilde{\lambda}$ obtained from buy orders in NYSE/AMEX-listed stocks is 3.47.[23] We want to compare the estimated price impact using Obizhaeva's estimate of $\tilde{\lambda} = 3.47$ based on buy orders to our estimates because the issuers must buy the underlying stocks to hedge the SPARQS and STRIDES.

To do this, we combine Obizhaeva's estimate of $\tilde{\lambda} = 3.47$ with the characteristics of the underlying stocks of the SPARQS and STRIDES in order to see what price impact is implied by her estimate of $\tilde{\lambda} = 3.47$. Disregarding the random component $d\widetilde{Z}_{t,i}$, for buy orders $\mathrm{I}_{BS,i} = 1$ and equation (11) can be rewritten as

$$\frac{dP_{t,i}}{P_{t,i}} = \tilde{\lambda} \times \sigma_{r,i} \times \frac{dX_{t,i}}{ADV_i}. \tag{12}$$

Our summary statistics for the SPARQS and STRIDES in Table 2 indicate that the median ratios of the proceeds to the market capitalizations of the underlying stocks are 0.096% and 0.085% for the SPARQS and STRIDES, respectively. Multiplying by the typical elasticity of 0.4, the ratios of the dollar amount of required hedging trade to market capitalization are $0.4 \times 0.096\% = 0.0384\%$ and $0.4 \times 0.085\% = 0.0340\%$, respectively. Letting M_i denote the number of outstanding shares for the ith underlying stock, in our sample the ratio $(P_i \times dX_{t,i})/(P_i \times M_i) = dX_{t,i}/M_i$ is typically roughly 0.0384% or 0.0340% for the SPARQS and STRIDES, respectively. Table 2 also reveals that the median values of daily turnover, defined as ADV_i/M_i, are 1.17% and 1.19% for the SPARQS and STRIDES, respectively. The price impact is then estimated as

$$\begin{aligned}
\frac{dP_{t,i}}{P_{t,i}} &= \tilde{\lambda} \times \sigma_{r,i} \times \frac{dX_{t,i}}{ADV_i} && (13)\\
&= \tilde{\lambda} \times \sigma_{r,i} \times \frac{dX_{t,i}}{M_i} \times \frac{M_i}{ADV_i} && (14)\\
&= 3.47 \times \sigma_{r,i} \times 0.0384\% \times \frac{1}{1.17\%} && (15)\\
&= 0.114 \times \sigma_{r,i} && (16)
\end{aligned}$$

for the SPARQS and

$$\begin{aligned}
\frac{dP_{t,i}}{P_{t,i}} &= 3.47 \times \sigma_{r,i} \times 0.0340\% \times \frac{1}{1.17\%} && (17)\\
&= 0.101 \times \sigma_{r,i} && (18)
\end{aligned}$$

[23] See the estimates of $\tilde{\lambda}$ for various sets of orders for the group "$adv10$" toward the top of Table 3 on p. 34 of the March 22, 2009 version of Obizhaeva (2009). The estimate based on buy orders in NASDAQ-listed stocks is 0.98, and is an exception to the general pattern that the estimated price impact is larger for stocks with higher trading volume. However, the price impact parameter for high-volume NASDAQ-listed stocks is estimated imprecisely, with a 95% confidence interval that appears to extend out to about 6 (see Figure 3, Panel A, the third graph in the row).

for the STRIDES, respectively. If $\sigma_{r,i} \approx 0.04$ then these imply price impacts of somewhat above 40 basis points. These are roughly one-half and one-third of the day 1 reversals for the SPARQS and STRIDES underlying stocks reported in our analysis of the price impact of SEPs hedging trades.

The difference is likely at least partially due to the fact that Obizhaeva (2009) finds that the price impact parameter is increasing in average daily volume, and the average daily volume of the SPARQS' and STRIDES' underlying stocks is actually greater than the average daily volume in Obizhaeva (2009)'s highest volume group "$adv10$." Specifically, the rightmost column in Table 1, Panel B of Obizhaeva (2009) shows that the average daily volume for her high-volume group "$adv10$" is about \$200 million.[24] For the SPARQS' and STRIDES' underlying stocks, average daily volume computed as the product of the median daily turnover and median market capitalization from Table 2 are about \$272 and \$486 million, respectively. Also, the portfolio transitions studied in Obizhaeva (2009) are typically executed over multiple days, in contrast to the SEPs' hedging trades that are executed over only one day, with a large fraction of the trading occurring in the 30 minutes prior to the close of trading. To the extent that high-volume stocks display resilience one would expect the price impact of the portfolio transitions executed over multiple days to be smaller.[25] In light of these factors, the differences in the estimates of the price impact seem plausible.

[24]Elsewhere in Obizhaeva (2009) average daily volume seems to be measured in shares, not dollars, consistent with the equations above.

[25]It should also be noted that the point estimate of 3.47 in Obizhaeva (2009) is not particularly precise, as upper limit of the 95% confidence band is close to 7. Also, the 2001–2005 sample period in Obizhaeva (2009) includes only 5 of the 9 years in the 2001–2009 sample used for the SEPs, and it is possible that this plays a role in the difference in the estimates of the price impact.

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Appendix A Computation of Standard Errors

Testing the significance of the cumulative average residual returns (CARRs) described in Equation (4) of Section 3, which are computed from the market model for the underlying stocks in Equation (1), involves computing the variance of the cumulative averages of the form

$$\sum_{t=1}^{L}\left(\frac{1}{N}\sum_{i=1}^{N}\varepsilon_{i,\tau_i+t}\right), \tag{A.1}$$

where $\tau_i + t$ is a calendar date. We make the following assumptions about the residuals:

$$\begin{aligned}
\operatorname{var}(\varepsilon_{i,\tau_i+t}) &= \sigma_i^2, & \text{(A.2)}\\
\operatorname{cov}(\varepsilon_{i,\tau_i+t}, \varepsilon_{j,\tau_i+t}) &= \rho_{ij}\sigma_i\sigma_j, & \text{(A.3)}\\
\operatorname{cov}(\varepsilon_{i,\tau_i+t}, \varepsilon_{i,\tau_i+u}) &= 0 \quad \text{for } \tau_i + t \neq \tau_i + u, & \text{(A.4)}\\
\operatorname{cov}(\varepsilon_{i,\tau_i+t}, \varepsilon_{j,\tau_i+u}) &= 0 \quad \text{for } \tau_j + u \neq \tau_i + t. & \text{(A.5)}
\end{aligned}$$

Comparing (A.2) to (A.4) and (A.3) to (A.5), one can see that the covariance differs depending upon whether the time indices of the ε's are the same. Let $I(v, w)$ be the indicator function taking the value 1 if $w = v$, and 0 otherwise. The variance of the sum (A.1) is

$$\begin{aligned}
&\operatorname{var}\left[\sum_{t=1}^{L}\frac{1}{N}\sum_{i=1}^{N}\varepsilon_{i,\tau_i+t}\right]\\
&= \sum_{t=1}^{L}\sum_{u=1}^{L}\frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N}\operatorname{cov}(\varepsilon_{i,\tau_i+t}, \varepsilon_{j,\tau_j+u}) & \text{(A.6)}\\
&= \sum_{t=1}^{L}\sum_{1=0}^{L}\frac{1}{N^2}\sum_{i=1}^{N}\sum_{j=1}^{N}\rho_{ij}\sigma_i\sigma_j I(\tau_i + t, \tau_j + u), & \text{(A.7)}
\end{aligned}$$

where if $i = j$ (the same issue) then $\rho_{ij} = 1$. To compute the right-hand side of (A.7) we estimated σ_i, σ_j, and ρ_{ij} from the returns over the first 150 post-event days following the ith and jth issues. This involves computing σ_j from the 150 post-event days following the jth issue, and computing ρ_{ij} from the overlapping days. If there is no overlap in the ith and jth post-event windows, then there is no need to calculate ρ_{ij}. After computing the right-hand side of equation (A.7), the standard error is simply the square root of the variance and the t-statistic is straightforward.

Table 1: Underlying Stocks of the SPARQS and STRIDES

Descriptive statistics for the underlying stocks of the SPARQS and STRIDES. Panel A lists the stocks referenced by at least three SPARQS or STRIDES. Panel B provides the proportions of the underlying stocks that fall into each market-capitalization quintile, and also the largest decile. In Panel B, each underlying stock is assigned to a NYSE market capitalization quintile or decile based on its market capitalization on the last day of the month immediately preceding the structured product pricing date. Market capitalization is defined as the product of shares outstanding and the last price, with both of these taken from the CRSP daily file.

Panel A: Most Frequent Underlying Stocks

Sample Observations	Company Name	Number SPARQS	Number STRIDES
11	APPLE	9	2
6	INTEL	4	2
5	CISCO SYSTEMS	1	4
4	EMC	2	2
4	TEXAS INSTRUMENTS	3	1
4	BEST BUY	2	2
4	VALERO ENERGY	4	0
4	YAHOO	3	1
4	NVIDIA	4	0
3	CORNING	2	1
3	QUALCOMM	2	1
3	DELL COMPUTER	2	1
3	JUNIPER NETWORKS	3	0
3	BOEING	1	2
3	AT&T	3	0
3	XILINX	2	1
3	WEATHERFORD INTERNATIONAL	3	0
3	MONSANTO	2	1
3	NATIONAL SEMICONDUCTOR	3	0
3	EXXON MOBIL	2	1

Panel B: Size Quintile Distribution of Underlying Stocks

Structured Product	Smallest Quintile	2	3	4	Largest Quintile	Largest Decile
SPARQS and STRIDES	0.00%	0.00%	1.16%	12.72%	86.13%	64.74%
SPARQS	0.00%	0.00%	0.81%	16.13%	82.06%	60.48%
STRIDES	0.00%	0.00%	2.04%	4.08%	93.88%	75.51%

Table 2: Characteristics of the SPARQS and STRIDES

Descriptive statistics of the two structured products in this study, Morgan Stanley's SPARQS and Merrill Lynch's STRIDES. The sample consists of all SPARQS and STRIDES issues through June 2009, with the except of two STRIDES based on indices. (The last STRIDES was priced in August 2008 and issued in September 2008, prior to Bank of America's acquisition of Merrill Lynch.) Issue-level details come from the pricing supplements available from the S.E.C.'s EDGAR database. The table presents the mean, median, maximum, and minimum coupon rates, days to first call, yield-to-call, original days to final maturity, and proceeds of the SEPs. The table also reports the statistics for the ratio of the issue proceeds to the market capitalization of the underlying stock, and the market capitalization and turnover of the underlying stock. Market capitalization is defined as the product of the closing stock price and the number of shares outstanding on the date immediately preceding the SEP's pricing date. The daily turnover is measured as the ratio of the average daily trading volume over the 21 trade days immediately preceding the pricing date divided by the shares oustanding as of the day before the pricing date. The shares outstanding, price, and trading volume data come from the CRSP daily file.

Issue Characteristics of the SPARQS and STRIDES

	Coupon Rate	Days to First Call	Yield-to-Call	Days to Maturity	Proceeds ($)	Ratio of Proceeds to Market Cap	Market Capitalization	Daily Turnover
SPARQS: Sample Size = 124								
Mean	8.88%	211.52	22.48%	402.89	25,506,616	0.188%	45,971,038,200	1.73%
Median	8.00%	201.00	20.00%	385.00	20,227,964	0.096%	23,323,071,490	1.17%
Maximum	16.00%	368.00	53.00%	719.00	136,500,000	1.421%	503,363,863,380	6.38%
Minimum	6.00%	180.00	15.00%	364.00	861,551	0.001%	1,632,424,710	0.38%
STRIDES: Sample Size = 49								
Mean	8.13%	318.63	19.31%	638.16	50,402,122	0.216%	68,047,941,066	1.44%
Median	8.00%	366.50	17.00%	731.00	37,500,000	0.085%	39,322,451,960	1.19%
Maximum	12.00%	369.00	42.00%	1,096.00	163,020,000	1.736%	475,203,728,160	5.68%
Minimum	5.75%	182.00	11.00%	365.00	14,124,000	0.020%	1,440,095,800	0.24%

Table 3: Average Returns of Underlying Stocks Around the Pricing Dates

Average raw and market-adjusted returns of the underlying common stocks on and around the pricing dates of the SPARQS and STRIDES. Dates are relative to the pricing dates, e.g. date 0 is the pricing date and date t is the date t days after (or before, if $t < 0$) the pricing date. Market-adjusted return are computed using the return on the CRSP value-weighted index, that is the market-adjusted return for underlying stock i on day t is $r_{i,t} - r_{M,t}$, where $r_{M,t}$ is the return on the CRSP value-weighted index on day t.
The first row of results in Panel A shows the average returns on the underlying stocks of the full sample of both SPARQS and STRIDES from 5 days before to 5 days after the pricing date. The t-statistics for the tests of the hypothesis that the average returns are equal to zero are in parentheses below the average returns. The next two rows present the average market-adjusted returns on the underlying stocks and the associated t-statistics. After these the table presents the number of market-adjusted returns that are positive and negative on each day. The last row provides the probability that the number of positive market-adjusted returns equals or exceeds the number of positive market-adjusted returns reported in the table under the null hypothesis that the probability of a positive return is 0.5. Specifically, the probability reported for day t is $\text{Prob}(k \geq x_t) = \sum_{k=x}^{n} \binom{n}{k} p^k (1-p)^{n-k}$, where x_t is the number of positive market-adjusted returns observed on day t, $\binom{n}{k} p^k (1-p)^{n-k}$ is the probability of k positive returns out of a total of n returns, and $p = 0.5$ is the probability of a positive return under the null hypothesis. In Panel A the sample size is $n = 173$. Panels B and C present the corresponding results for the subsamples of SPARQS ($n_{SPARQS} = 124$) and STRIDES ($n_{STRIDES} = 49$), respectively.

Panel A: Full Sample

Day relative to pricing date	−5	−4	−3	−2	−1	**0**	1	2	3	4	5
Average return	0.0016	0.0024	0.0034	0.0008	0.0004	**0.0103**	−0.0079	0.0003	−0.0009	0.0008	0.0020
t-statistic	(0.70)	(1.15)	(1.66)	(0.37)	(0.20)	**(4.94)**	(−4.33)	(0.15)	(−0.45)	(0.37)	(1.21)
Average mkt.-adj. return	0.0001	0.0025	0.0029	0.0006	0.0015	**0.0095**	−0.0074	−0.0012	−0.0021	0.0007	0.0019
t-statistic	(−0.06)	(1.38)	(1.74)	(0.32)	(0.86)	**(5.16)**	(−4.68)	(−0.78)	(−1.23)	(0.37)	(1.47)
Number mkt.-adj. ret. > 0	87	93	88	84	94	**112**	58	84	81	90	90
Number mkt.-adj. ret. < 0	86	80	85	89	79	**61**	115	89	92	83	83
Probability under H_0	0.5000	0.1808	0.4396	0.6758	0.1436	**0.0001**	1.0000	0.6758	0.8192	0.3242	0.3242

Panel B: SPARQS

Day relative to pricing date	−5	−4	−3	−2	−1	**0**	1	2	3	4	5
Average return	0.0018	0.0018	0.0012	0.0004	0.0036	**0.0079**	−0.0058	0.0009	−0.0016	0.0017	0.0031
t-statistic	(0.71)	(0.76)	(0.53)	(0.14)	(1.54)	**(3.70)**	(−3.01)	(0.40)	(−0.71)	(0.75)	(1.63)
Average mkt.-adj. return	−0.0002	0.0025	0.0017	0.0003	0.0043	**0.0076**	−0.0055	−0.0009	−0.0031	0.0014	0.0030
t-statistic	(−0.09)	(1.24)	(0.87)	(0.13)	(2.16)	**(3.90)**	(−3.22)	(−0.51)	(−1.45)	(0.71)	(2.02)
Number mkt.-adj. rets. > 0	63	67	59	63	70	**78**	44	60	57	64	71
Number mkt.-adj. rets. < 0	61	57	65	61	54	**46**	80	64	67	60	53
Probability under H_0	0.4642	0.2095	0.7351	0.4642	0.0889	**0.0026**	0.9996	0.6732	0.8384	0.3939	0.0633

Panel C: STRIDES

Day relative to pricing date	−5	−4	−3	−2	−1	0	1	2	3	4	5
Average return	0.0009	0.0039	0.0088	0.0019	−0.0075	**0.0161**	−0.0131	-0.0014	0.0010	−0.0015	−0.0008
t-statistic	(0.20)	(0.90)	(2.11)	(0.55)	(−1.76)	**(3.28)**	(−3.17)	(−0.38)	(0.28)	(−0.29)	(−0.26)
Average market-adjusted return	0.0001	0.0023	0.0060	0.0013	−0.0054	**0.0143**	−0.0119	−0.0018	0.0001	−0.0011	−0.0011
t-statistic	(0.02)	(0.62)	(1.86)	(0.47)	(−1.49)	**(3.41)**	(−3.53)	(−0.67)	(0.05)	(−0.26)	(−0.45)
Number mkt.-adj. ret. > 0	24	26	29	21	24	**34**	14	24	24	26	19
Number mkt.-adj. ret. < 0	25	23	20	28	25	**15**	35	25	25	23	30
Probability under H_0	0.6123	0.3877	0.1264	0.8736	0.6123	**0.0047**	0.9993	0.6123	0.6123	0.3877	0.9573

Table 4: Average Returns of SPARQS' Underlying Stocks Around the Filing Dates of the Preliminary Pricing Supplements and the Pricing Dates

Panel A presents the average raw and market-adjusted returns of the SPARQS' underlying common stocks on and around the filing dates of the SPARQS' preliminary pricing supplements, for the 66 preliminary pricing supplements that were filed. Dates are relative to filing date, e.g. date 0 is the filing date. Market-adjusted returns are computed using the returns on the CRSP value-weighted index, that is the market-adjusted return for underlying stock i on day t is $r_{i,t} - r_{M,t}$, where $r_{M,t}$ is the return on the CRSP value-weighted index on day t.

The first row of results shows the average returns on the underlying stocks from 5 days before to 5 days after the filing date of the preliminary pricing supplements. The t-statistics for the tests of the hypothesis that the average returns are equal to zero are in parentheses below the average returns. The next two rows present the average market-adjusted returns on the underlying stocks and the associated t-statistics. After these the table presents the number of market-adjusted returns that are positive and negative on each day. The last row provides the probability that the number of positive market-adjusted returns equals or exceeds the number of positive market-adjusted returns reported in the table under the null hypothesis that the probability of a positive return is 0.5. Specifically, the probability reported for day t is $\text{Prob}(k \geq x_t) = \sum_{k=x}^{n} \binom{n}{k} p^k (1-p)^{n-k}$, where x_t is the number of positive market-adjusted returns observed on day t, $\binom{n}{k} p^k (1-p)^{n-k}$ is the probability of k positive returns out of a total of n returns, and $p = 0.5$ is the probability of a positive return under the null hypothesis.

Panel B presents the average returns around the filing dates, adjusted for the average return on the sample stocks over the preceding 10 days. Specifically, for event date t the table presents the average returns $(1/66)\sum_{i=1}^{66}(r_{i,t} - \mu(t-10,t-1)$ and $(1/66)\sum_{i=1}^{66}(r_{i,t} - r_{M,t} - m(t-10,t-1)$, where $\mu(t-10,t-1) = (1/660)\sum_{k=1}^{10}\sum_{i=1}^{66} r_{i,t-k}$ and $m(t-10,t-1) = (1/660)\sum_{k=1}^{10}\sum_{i=1}^{66}(r_{i,t-k} - r_{M,t-k})$.

Panel C presents the average raw and market-adjusted returns of the underlying common stocks on and around the SPARQS'pricing dates, for the subset of 59 SPARQS issues for which preliminary pricing supplements were filed. (7 of the 66 preliminary pricing supplements that determine the samples used in Panels A and B were not followed by SPARQS issues.) Dates in Panel C are relative to the pricing dates.

Panel A: Returns on and Around the Filing Date

Day relative to filing date	−5	−4	−3	−2	−1	0	1	2	3	4	5
Average return	0.0022	0.0004	0.0031	0.0048	0.0024	0.0049	−0.0002	0.0009	0.0077	−0.0014	0.0045
t-statistic	0.7076	0.1322	1.0345	1.5696	0.7840	1.5570	−0.0548	0.2565	1.9690	−0.3812	0.9935
Average market-adjusted return	0.0030	−0.0008	0.0029	0.0031	0.0008	0.0034	−0.0014	−0.0011	0.0072	−0.0024	0.0039
t-statistic	1.0658	-0.3152	1.1555	1.2695	0.2921	1.3530	−0.5121	−0.3737	2.0189	−0.7518	0.9378
Number mkt.-adj. ret. > 0	38	34	37	37	31	40	31	36	36	34	38
Number mkt.-adj. ret. < 0	28	32	29	29	35	26	35	30	30	32	28
Probability under H_0	0.1339	0.4511	0.1945	0.1945	0.7307	0.0544	0.7307	0.2693	0.2693	0.4511	0.1339

Panel B: Returns on and Around the Filing Date Using Prior Average Returns as Benchmark

Day relative to filing date	−5	−4	−3	−2	−1	0	1	2	3	4	5
Average return	0.0007	−0.0010	0.0013	0.0028	−0.0002	0.0031	−0.0002	0.0009	0.0077	−0.0014	0.0045
t-statistic	0.2093	−0.3630	0.4234	0.9144	−0.0559	0.9752	−0.0548	0.2565	1.9690	−0.3812	0.9935
Average market-adjusted return	0.0000	−0.0023	0.0012	0.0013	−0.0014	0.0019	−0.0014	−0.0011	0.0072	−0.0024	0.0039
t-statistic	0.0000	−0.8782	0.4733	0.5483	−0.5429	0.7542	−0.5121	−0.3737	2.0189	−0.7518	0.9378
Number mkt.-adj. ret. > 0	35	31	34	34	26	37	31	36	36	34	38
Number mkt.-adj. ret. < 0	31	35	32	32	40	29	35	30	30	32	28
Probability under H_0	0.3561	0.7307	0.4511	0.4511	0.9680	0.1945	0.7307	0.2693	0.2693	0.4511	0.1339

Panel C: Returns on and Around the Pricing Date

Day relative to pricing date	−5	−4	−3	−2	−1	0	1	2	3	4	5
Average return	−0.0001	−0.0001	0.0027	−0.0001	0.0025	0.0072	−0.0035	0.0010	−0.0029	−0.0006	0.0046
t-statistic	(−0.04)	(−0.03)	(0.92)	(−0.03)	(1.00)	(2.36)	(−1.34)	(0.31)	(−0.81)	(−0.17)	(2.32)
Average market-adjusted return	−0.0010	0.0000	0.0003	0.0021	0.0020	0.0060	−0.0038	0.0001	−0.0044	−0.0006	0.0039
t-statistic	(−0.40)	(0.01)	(0.13)	(0.83)	(0.89)	(2.23)	(−1.59)	(0.03)	(−1.25)	(−0.24)	(2.43)
Number mkt.-adj. ret. > 0	30	28	27	33	32	34	21	31	26	30	37
Number mkt.-adj. ret. < 0	29	31	32	26	27	25	38	28	33	29	22
Probability under H_0	0.5000	0.6985	0.7825	0.2175	0.3015	0.1488	0.9908	0.3974	0.8512	0.5000	0.0337

Table 5: Underlying Stocks Post-Issue Cumulative Average Residual Returns

Post-issue return performance of the underlying stocks of the SPARQS and STRIDES evaluated using cumulative average residual returns (CARRs) based on three benchmark models. For the ith SPARQS or STRIDES issue, the excess returns to the underlying reference equity, $r_{i,t} - r_t$, under the three benchmark models are:

$$\begin{aligned} r_{i,t} - r_t &= \beta_i(r_{M,t} - r_t) + \varepsilon_{i,t}, \\ r_{i,t} - r_t &= \beta_i(r_{M,t} - r_t) + s_i(SMB_t) + h_i(HML_t) + \varepsilon_{i,t}, \\ r_{i,t} - r_t &= \beta_i(r_{M,t} - r_t) + s_i(SMB_t) + h_i(HML_t) + m_i(MO_t) + \varepsilon_{i,t}, \end{aligned}$$

where $i = 1, \ldots, N$ indexes the reference equities, $r_{M,t} - r_t$ is the excess return on the market portfolio over the risk-free rate, SMB_t is the return on small stocks over large stocks, HML_t is the return on high book-to-market firms over low book-to-market firms,and MO_t is the return on high momentum stocks over low momentum stocks. The parameters β_i, s_i, h_i, and m_i are the loadings on the market, size, book-to-market, and momentum factors, respectively. The factor loadings are estimated from the immediately preceding 60 monthly returns when 60 returns are available. If between 30 and 59 monthly returns are available, the factor loadings are estimated using all available returns. Stocks for which fewer than 30 preceding monthly returns are available are dropped from the sample. The table presents the event-time CARRs, standard errors, t-statistics, and sample sizes for the two hundred trade dates following the pricing dates.

Post-Issue Performance of Underlying Stocks

	Trading Days After Issue, Cumulative Average Residual Returns											
	+1	+2	+20	+40	+60	+80	+100	+120	+140	+160	+180	+200
Market Model												
CARR ($\epsilon_{i,t}$)	−0.69%	−0.89%	−1.18%	0.36%	0.87%	0.39%	0.00%	0.30%	0.64%	0.57%	1.59%	2.33%
Standard Error	0.19%	0.27%	0.91%	1.42%	1.88%	2.33%	2.75%	3.15%	3.52%	3.90%	4.27%	4.64%
t-statistic	(−3.61)	(−3.27)	(−1.31)	(0.25)	(0.46)	(0.17)	(0.00)	(0.09)	(0.18)	(0.15)	(0.37)	(0.50)
Sample Size	169	169	169	169	169	169	169	169	168	167	166	165
Fama-French 3-factor Model												
CARR ($\epsilon_{i,t}$)	−0.76%	−0.93%	−0.45%	1.55%	2.63%	2.46%	2.28%	2.97%	3.57%	3.68%	4.59%	5.14%
Standard Error	0.19%	0.27%	0.88%	1.34%	1.77%	2.17%	2.55%	2.90%	3.24%	3.58%	3.91%	4.24%
t-statistic	(−3.98)	(−3.44)	(−0.51)	(1.15)	(1.49)	(1.13)	(0.89)	(1.02)	(1.10)	(1.03)	(1.17)	(1.21)
Sample Size	169	169	169	169	169	169	169	169	168	167	166	165
Carhart 4-factor Model												
CARR ($\epsilon_{i,t}$)	−0.75%	−0.94%	−0.53%	1.70%	2.80%	2.23%	2.16%	3.05%	3.90%	4.10%	5.55%	6.22%
Standard Error	0.19%	0.27%	0.88%	1.35%	1.77%	2.17%	2.54%	2.89%	3.22%	3.54%	3.87%	4.19%
t-statistic	(−3.90)	(−3.44)	(−0.60)	(1.26)	(1.58)	(1.03)	(0.85)	(1.06)	(1.21)	(1.16)	(1.43)	(1.49)
Sample Size	169	169	169	169	169	169	169	169	168	167	166	165

Table 6: Calendar Time Portfolio Return Regressions

Calendar time portfolio return regressions in which returns on portfolios of SPARQS and STRIDES underlying stocks are regressed on return factors using data from the period June 2001 through December 2009. Each month, the portfolio returns consist of equal-weighted returns on all reference equities for the SPARQS and STRIDES issued during the previous 200 trade days. The portfolio of underling stocks rebalances intra-month when stocks enter the portfolio on the day following a SEP pricing date and when stocks leave the portfolio after the 200th day following the pricing date.
Tests of abnormal returns are conducted using the market, three-factor, and four-factor regression models of the returns on the portfolio of underlying stocks. The regression equations are

$$
\begin{aligned}
r_{\Pi,t} - r_t &= \alpha + \beta \left(r_{M,t} - r_t\right) + \epsilon_t, \\
r_{\Pi,t} - r_t &= \alpha + \beta \left(r_{M,t} - r_t\right) + s\left(SMB_t\right) + h\left(HML_t\right) + \epsilon_t, \\
r_{\Pi,t} - r_t &= \alpha + \beta \left(r_{M,t} - r_t\right) + s\left(SMB_t\right) + h\left(HML_t\right) + m\left(MO_t\right) + \epsilon_t,
\end{aligned}
$$

where $r_{\Pi,t} - r_t$ is the monthly excess return on an equal-weighted portfolio of the underlying stocks, $r_{M,t} - r_t$ is the excess return on the CRSP value-weighted index, SMB_t is the monthly return of a small stock portfolio over a large stock portfolio, and HML_t is the monthly return of a high book-to-market stock portfolio over a low book-to-market portfolio, and MO_t is the monthly return of high momentum stocks over low momentum stocks. The table reports coefficient estimates and t-statistics in parenthesis. The sample consists of 103 monthly observations from June 2001, when the first SPARQS were issued, and ending in December 2009.

Calendar-Time Portfolio Return Regression Results

	Intercept	**Market**	**Size**	**Book-to-Market**	**Momentum**
Coefficient	−0.0005	1.4633			
t-statistic	(−0.106)	(13.398)			
Coefficient	0.0021	1.5218	0.1407	−0.9473	
t-statistic	(0.459)	(14.831)	(0.814)	(−5.590)	
Coefficient	0.0021	1.5406	0.1407	−0.9466	0.0254
t-statistic	(0.452)	(12.397)	(0.810)	(−5.559)	(0.271)

Table 7: Regressions of Price Impact on Measures of Liquidity

Coefficient estimates and t-statistics from regressions of the pricing date market-adjusted returns of the SEPs' underlying stocks on several measures of and proxies for (il)liquidity. The dependent variable is $r_{i0} - r_{M0}$, the market-adjusted return on the underlying stock of the i-th SEP issue on the pricing date $t = 0$. The liquidity measures c^{BMA}, γ_0, γ_1, and c^{Roll} are described in Hasbrouck (2006) and made available on his website http://pages.stern.nyu.edu/ jhasbrou/Research/GibbsEstimates2006/Liquidity%20estimates%202006.htm. c^{BMA} is the coefficient on the change in the trade direction indicator in the "basic market-adjusted" model (8), γ_0 and γ_1 are the intercept and slope coefficient in the latent common factor model (9), and c^{Roll} is the Roll (1984) trading cost estimator. The variable σ is the standard deviation of the returns on the underlying stock over the 20-day period prior to the pricing date, RelSize is the ratio of the total principal amount of the SEP issue to the market capitalization of the underlying stock as of the close of trading on the day before the pricing date, and STRIDES is a dummy variable taking the value 1 if the issue was a STRIDES. The sample used in these regressions consists of the subset of the total sample for which the Hasbrouck liquidity measures were available, a total of 94 issues during or prior to 2006.

Coefficient Estimates and t-statistics (in parentheses)

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Constant	0.0060	0.0058	0.0048	0.0049	0.0064	0.0044	0.0011
	(1.717)	(1.656)	(1.495)	(1.360)	(1.942)	(1.320)	(0.2557)
RelSize	0.0025	−0.0001	0.0006	0.0023	−0.0038	−0.0005	−0.0000
	(2.917)	(−0.079)	(0.219)	(2.676)	(−1.978)	(−0.176)	(−0.004)
$c^{\text{BMA}} \times$RelSize		0.7356				−1.2025	−1.1890
		(1.614)				(−1.504)	(−1.374)
$\gamma_0^{\text{LCF}} \times$RelSize			−0.3801			−0.4097	−0.3357
			(−0.603)			(−0.509)	(−0.390)
$\gamma_1^{\text{LCF}} \times$RelSize			0.3723			0.3369	0.3482
			(3.958)			(2.375)	(2.442)
$c^{\text{Roll}} \times$RelSize				0.1967		0.2376	0.1968
				(1.236)		(1.164)	(0.946)
$\sigma \times$RelSize					0.1996	0.1803	0.1672
					(3.642)	(2.829)	(2.583)
STRIDES							0.0085
							(1.305)
STRIDES$\times$RelSize							−0.0010
							(−0.562)
$\bar{R}^2$	0.0847	0.1102	0.2423	0.0998	0.2011	0.3107	0.3247

Figure 1: SPARQS' Cumulative Intraday Returns and Net Buying Volume

Average intraday cumulative market-adjusted returns (left scale) and net buying volume (right scale) for the SPARQS' underlying stocks during 5-minute intervals on the pricing date. The market-adjusted returns are computed relative to the return on the S&P Depositary Receipts (SPDRs, ticker symbol SPY). For each 5-minute interval, the return on the underlying stock is computed from (i) the price of a transaction that has a time stamp that falls within the interval and is at or closest to the end of the interval, and (ii) the closing price from the previous day. The SPDRs' returns are computed similarly. Net buying volume is estimated by classifying each trade as either a "buy" or "sell." Trades that occur at or above (below) the prevailing ask (bid) price are classified as "buy" ("sell") trades. Trades inside the quotes are classified according to the tick test, in which trades are classified "buys" if they occur on an uptick or zero uptick and "sells" if they occur on downticks or zero downticks. Following the Lee and Ready (1991) algorithm, we exclude all trades with special settlement conditions, and the prevailing quotes are computed from the most recent eligible quotes five seconds prior to the trade price. The net buying volume for each 5-minute interval is the sum of the buy and sell orders that have time stamps that fall within the interval, treating a sell as a negative buy, and the cumulative net buying volume is the sum of the net buying volume for the current interval and all previous intervals.

Figure 2: STRIDES' Cumulative Intraday Returns and Net Buying Volume

Average intraday cumulative market-adjusted returns (left scale) and intraday cumulative net buying volume (right scale) for the STRIDES' underlying stocks during 5-minute intervals on the pricing date. The market-adjusted returns are computed relative to the return on the S&P Depositary Receipts (SPDRs, ticker symbol SPY). For each 5-minute interval, the return on the underlying stock is computed from (i) the price of a transaction that has a time stamp that falls within the interval and is at or closest to the end of the interval, and (ii) the closing price from the previous day. Net buying volume is estimated by classifying each trade as either a "buy" or "sell." The SPDRs' returns are computed similarly. Net buying volume is estimated by classifying each trade as either a "buy" or "sell." Trades that occur at or above (below) the prevailing ask (bid) price are classified as "buy" ("sell") trades. Trades inside the quotes are classified according to the tick test, in which trades are classified "buys" if they occur on an uptick or zero uptick and "sells" if they occur on downticks or zero downticks. Following the Lee and Ready (1991) algorithm, we exclude all trades with special settlement conditions, and the prevailing quotes are computed from the most recent eligible quotes five seconds prior to the trade price. The net buying volume for each 5-minute interval is the sum of the buy and sell orders that have time stamps that fall within the interval, treating a sell as a negative buy, and the cumulative net buying volume is the sum of the net buying volume for the current interval and all previous intervals.