An Empirical Investigation of Volume in Equity-Contingent Claims

by

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Abstract

Little is known about the joint dynamics of volume across contingent claims. We study the time-series of trading activity in the cash S&P 500 index and its derivatives (options, the legacy and E-mini futures contracts, and the ETF), and consider their dynamic relation with the macroeconomy, over a long time-period of more than 3000 trading days. Legacy futures volume has trended downward while other series have trended upward. Total futures volume has shown an upward trend, suggesting that the trading in the E-mini contract has at least partially supplanted that in the legacy contract. All series are highly cross-correlated and jointly dependent. Signed and absolute trading activity in contingent claims (most prominently, options) predicts shifts in stock market volatility and aggregate state variables such as the short rate, and the term and credit spreads, as well as signed and absolute returns around major macroeconomic announcements. Overall, options markets appear to play the strongest informational role, in that options volume innovations seem to have the strongest forecasting ability for fluctuations in the macroeconomic environment.

Introduction

Securities markets are often characterized by multiple contingent claims on the same underlying asset. These claims allow for holding exposures to an asset at lower transaction costs with greater leverage, and in the case of options, in a non-linear fashion. Financial economists have made notable progress on how these claims should be priced relative to each other. But trading activity in such contracts warrants separate examination for at least two reasons. First, trading is a costly activity; the public transfers several billion dollars every year to intermediaries in the form of commissions and bid-ask spreads.[1] Second, there is evidence that increases in trading activity are associated with decreases in the cost of capital.[2]

While equity volume is well studied (e.g., Karpoff, 1987), comparatively little is known about the joint dynamics of derivatives and cash volume. For example, how correlated are the time-series of trading volumes across different contingent claims? How volatile are these time-series? Do some contingent claims attract more speculative activity and thus forecast the macroeconomy better than others? A comprehensive answer to questions such as these for all existing contingent claims is a daunting task, but we hope to take a first step by examining trading activity in the cash S&P 500 index *simultaneously* with that in four contingent claims on the index: options, legacy and E-Mini futures, and exchange traded funds.

In Black and Scholes (1973), options can be replicated in continuous time by investments in stocks and bonds. Options, however, are not redundant when the process for the underlying stock involves stochastic discontinuities (Naik and Lee, 1990; Pan and Liu, 2003). In general, when markets are incomplete, options cannot be replicated by trading in simple equity or fixed income securities; see the analyses of Ross (1976), Hakansson (1982), and Detemple and Selden (1991). All of these models, while insightful, do not explicitly model trading activity. But, trading in options is actually quite active.

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[1] In his AFA presidential address, French (2008) suggests that the cost of price discovery via trading was about $99 billion in 2006.
[2] See Datar, Naik, and Radcliffe (1998), and Brennan, Chordia and Subrahmanyam (1998).

Another line of research suggests that options markets may alter the incentives to trade on private information about the underlying asset. According to Cao (1999), informed agents should be able to trade more effectively in options that span more contingencies. In addition, informed traders may prefer to trade options rather than stock, because of increased leverage (Back, 1992).[3] Cao and Wei (2010) find evidence that information asymmetry is greater for options than for the underlying stock, implying that informed agents prefer options. This finding is supported by Easley, O'Hara, and Srinivas (1998), Chakravarty, Gulen, and Mayhew (2004), and Pan and Poteshman (2006), who find that options orders contain information about future stock prices. Ni, Pan, and Poteshman (2008) show that options order flow forecasts stock volatility. Anthony (1988) indicates that option volume leads stock volume. Cao, Chen, and Griffin (2005) demonstrate that options volume predicts returns around takeover announcements, suggesting the presence of informed traders in the options market prior to corporate events.

In sum, the preceding literature suggests that options markets stimulate informed trading. It also is well known that options are used for hedging positions in other options as well as in the underlying stock.[4] Thus, the literature indicates that options volume could arise both for informational as well as risk-sharing reasons. Since volume in the underlying stock could also arise for similar reasons, the question arises as to what factors explain the trading activity in options markets relative to the stock market. Motivated by this observation, in a recent study, Roll, Schwartz, and Subrahmanyam (2010) analyze whether the ratio of equity options volume relative to the underlying stock volume is related to hedging and informational proxies. Nevertheless, no studies have analyzed options volume dynamics in conjunction with trading activity in the cash market as well as in *other* equity derivatives. This issue is pertinent because it needs to be investigated whether or not the informational role of options dominates that of other contingent claims.

Turning now to index futures contracts, these would also be redundant in a frictionless world, but Gorton and Pennachi (1993) and Subrahmanyam (1991) indicate that futures may

[3] Figlewski and Webb (1993), Danielsen and Sorescu (2001), and Ofek, Richardson, and Whitelaw (2004) explore the role of options in alleviating short-selling constraints.
[4] Lakonishok, Lee, Pearson, and Poteshman (2007) show that covered call writing, a form of hedging, is one of the most commonly used strategies in options markets.

provide a preferred venue for uninformed traders by removing sensitivity to firm-specific informational asymmetries. Along these lines, Daigler and Wiley (1999) find that futures volatility is primarily caused by (presumably uninformed) members of the general public. Roll, Schwartz, and Subrahmanyam (2007) find that the liquidity of the underlying index influences the pricing gap between the theoretical and observed basis, but they do not analyze volume. Allaying concerns that derivatives may attract too many uninformed agents and cause volatility spillovers to the stock market, Bessembinder and Seguin (1992) find that futures volume only has a limited impact on stock volatility. We add to these studies by considering the relation between index futures markets and *alternative* equity derivatives.

With regard to exchange-traded funds (ETFs), the third type of contingent claim we analyze, Hasbrouck (2003) uses transactions data to examine the linkages between ETFs and index futures contracts. The focus in Hasbrouck (2003) is on prices, rather than trading activity; he shows that index futures dominate ETFs in price discovery. We build on Hasbrouck's (2003) work by considering ETF *volume* vis-à-vis prices and volume in the underlying index, *and* in relation to volume in other derivatives markets such as those for futures and options. However, unlike Hasbrouck's (2003) study of intraday price formation, we use data aggregated at daily intervals.

As for cash volume, there have been previous time-series studies of equity trading activity, many of which have focused on short-term patterns in volume or on the contemporaneous links between volume and other variables such as return volatility. Thus, a number of empirical papers have documented a positive correlation between volume and absolute price changes (see Karpoff, 1987, Schwert, 1989, and Gallant, Rossi, and Tauchen, 1992). Other papers document time-series regularities: Amihud and Mendelson (1987, 1991) find that volume is higher at the market's open, while Foster and Viswanathan (1993) demonstrate a U-shaped intraday volume pattern and also find that trading volume is lower on Mondays. In another stream of research, Campbell, Grossman, and Wang (1993) and Llorente, Michaely, Saar, and Wang (2002) analyze the dynamic relation between returns and volume levels. Chordia, Roll, and Subrahmanyam (2011) consider the causes of the recent trend in trading activity and conclude that it is mainly due to a rise in institutional trading, but they do not consider trends in contingent claims volume.

In contrast to previous work on trading activity, which has mostly analyzed volume in equities or in the context of a single contingent claim, we conduct an empirical study of the joint time-series of volume in the underlying S&P 500 index, the associated ETF, index futures (the legacy contract as well as the newer E-mini contract), and index options. Unfortunately, there is a paucity of theoretical work on the joint dynamics of trading activity in multiple contingent claims, which precludes the development of sharp testable hypotheses. We instead conduct an exploratory empirical study. Beyond analyzing basic time-series properties of the volume data, we aim to shed some light on the following issues (we first pose the question and then present the economic motivation):

- Are these claims substitutes or complements to each other and the cash market? Specifically, if one claim gains popularity and acts as a substitute for another, then it should drain volume away from another, so that volumes may exhibit opposing trends. On the other hand if contingent claims act as complementary hedging vehicles and as venues for efficiency-enhancing arbitrage trades, then volumes should exhibit common trends.
- Do volume innovations in one market lead other volume series? If derivatives attract informed agents due to lower transaction costs and enhanced leverage, then shocks to trading activity in derivatives should forecast those in the cash market, as arbitrageurs trade to close the gap in the cash market with a lag.
- Perhaps most importantly, does trading activity across different contingent claims differentially forecast macroeconomic states? Some contracts have small contract sizes (e.g., the E-mini and the ETF) and may cater to less-sophisticated retail clienteles. These contracts may play a less material role in forecasting macroeconomic conditions. On the other hand, if options are particularly attractive to agents because of their non-linear payoffs, then we would expect to see a greater economic role for options trading activity in forecasting macroeconomic conditions.

For addressing the preceding issues, we use data that span a long period, encompassing more than 3000 trading days, which allows for sufficient statistical power in uncovering reliable patterns in these time-series. To the best of our knowledge, our paper represents the first attempt to analyze trading activity that spans the cash equity market as well as multiple contingent claims on equities.

We find that all volume series (cash as well as contingent claims) fluctuate significantly from day to day, but fluctuations in derivatives markets are higher than those in the cash market. Further, daily changes in futures, cash, options, and ETF volumes are strongly and positively correlated. We also consider the time-series properties of trading activity across the four contingent claims and the cash index. Our results reveal that regularities are not common to all series. For example, while all series exhibit lower volumes at the beginning of the week, there is a reliable January seasonal in cash index volume, indicating higher trading activity in January, which is not as evident in the other series. This provides support for the notion that year-end cash inflows stimulate cash equity investments (Ogden, 1990). We also find that cash, options, E-mini futures, and ETF volumes have trended upward, but legacy futures volume has trended downward, indicating that the E-mini contract has become ever-more popular, likely due to its electronic trading protocol (Glosten, 1994) and small contract size, as opposed to the floor-based legacy contract. The combined E-mini and legacy volume, however, shows a strong upward trend. On aggregate, all contracts seem complementary to each other, demonstrating a strong upward trend in their trading activity.

We conduct a vector autoregression to examine the dynamics of the five volume series. This provides reliable evidence of joint determination. Specifically, contemporaneous correlations in VAR innovations are strongly positive across all of the markets, and Granger causality results as well as impulse response functions confirm that while the volume series are jointly dependent; no one series dominates in forecasting others. Following the vector autoregression, we consider the economic question of how contingent claims volume relates to the dynamics of the macroeconomy. Specifically, we consider how trading activity in the derivatives and the cash market is related to equity price formation and shifts in variables that capture macroeconomic states. We uncover evidence that options volume predicts absolute changes in the term structure and the credit spread. In addition, legacy futures volume predicts absolute shifts in the short rate and the term structure. Moreover, volume in these claims forecasts stock market volatility after accounting for volatility persistence. There also is evidence that options volume predicts absolute returns around major macroeconomic announcements. The role of cash index volume in predicting shifts in macroeconomic variables and returns around macroeconomic news releases is quite limited. This underscores the notion that derivatives, owing to their lower trading costs and enhanced leverage, play a key informational role.

Finally, we consider imputed signed volume, which potentially may capture the sign of speculative activity (Kyle, 1985), and thus signal the direction of shifts in macroeconomic states.[5] Since intraday data on contingent claims are hard to obtain for a long period, we sign the volume series by multiplying it by the sign of the daily return on the relevant contracts (following Pastor and Stambaugh, 2003). We first show that signed options volume reliably predicts signed equity market returns following major macroeconomic announcements. We next perform a vector autoregression with the signed volume series and signed daily shifts in macroeconomic variables. Granger causality results as well as impulse response functions confirm the dominance of the options market in forecasting the macroeconomic environment. Specifically, innovations to options volume forecast shifts in all the macroeconomic variables, whereas the forecasting ability of other volume series is more mixed. The analysis is consistent with speculative trading in options; it suggests that net bearish trading in options forecasts a decline in the macroeconomic environment and vice versa. Overall, the picture that emerges from our analysis is the dominance of options volume in forecasting shifts in the macroeconomic environment.

The remainder of this paper is organized as follows. Section I describes the data. Section II presents the regressions intended to address calendar regularities and trends in the time-series of trading activity. Section III describes the vector autoregressions. Section IV describes the role of the volume series in predicting shifts in macroeconomic variables and returns around

[5] In the Kyle (1985) model, prices are martingales and linear functions of signed order flow, so that order flow does not predict future innovations in public information (including future prices). However, if information about derivatives order flow is costly to access and therefore is not public information, it may predict future public signals even if the market is efficient in a semi-strong sense (Fama, 1970).

macroeconomic announcements. Section V considers the role of imputed signed volume. Section VI concludes.

I. Data

The data are obtained from several sources. First, index options data are from OptionMetrics. This database provides the daily number of contracts traded for each option on the S&P 500 index. We approximate the total daily options volume by multiplying the total contracts traded in each index option by the end-of-day quote midpoints[6] and then aggregating across all options listed on the index.

CRSP has volume data for the S&P 500 and the S&P 500 ETF (SPDR). The S&P500 index (or cash) volume series is created by value-weighting individual stock volume for all stocks in the index every day, using value weights as of the end of the previous day. In creating this volume series, an important issue is the treatment of Nasdaq volume. Atkins and Dyl (1997) indicate that Nasdaq trading activity is overstated because of double counting of interdealer trading. Anderson and Dyl (2005), however, argue that in recent times, due to the rise of public limit orders and Electronic Communication Network (ECN) trades reported on Nasdaq, the double-counting problem has been mitigated. They examine the trading of firms that switched from the Nasdaq to the NYSE in the 1997-2002 time period and find that median volume drops by about 37%, which is less than the 50% number found by Atkins and Dyl (1997). We therefore scale Nasdaq volume by the implied adjustment factor of 1.59 (=100/63) prior to its inclusion in aggregated S&P500 cash volume.

Data on index futures are obtained from Price-data.com. The legacy and E-Mini index futures volume series are constructed by simply adding contract volume across all contracts trading on a particular day. In the empirical analysis, all of the raw series are adjusted for

[6] Because of the difficulties involved in aggregating options of different maturities and strike prices, options volume is imputed in dollars for each option and then cumulated across options. This creates the possibly that options volume dynamics could be driven by shifts in prices, rather than quantities traded. However, we have verified that the results are qualitatively similar when we calculate options volume by simply summing the traded quantities across options.

various time-series regularities including indicator variables around expiration dates. Given that E-mini futures contracts started trading on September 9, 1997, we use daily data starting from this date to December 31, 2009, i.e., more than 3000 trading days.

Table 1 provides summary statistics for the basic volume series. The volumes are those reported by the data source, and each contract has a different associated multiplier. Thus, ETFs (SPDRs) trade in units of one-tenth of the index and futures trade in units of 250 times the index.[7] Further, E-Mini futures trade in units of 50 times the index. These scale factors need to be borne in mind while comparing the levels of volume across the different contracts. For the cash and legacy futures volumes, the means are fairly close to the medians, thus indicating little skewness. There is some evidence, however, of skewness for the E-Mini, options, and ETF volumes.

In Panel B of Table 1, we consider basic statistics for absolute proportional changes in volume (in percentages). Options volume fluctuates the most from day to day while cash volume fluctuates the least. The percentage daily changes in volume are quite large, ranging from 13.3% per day for the cash market to 38% for the options market. The larger fluctuations in derivatives relative to cash volume are consistent with informational flows being reflected in derivatives markets. Specifically, if volume arises at least partly due to the arrival of new information (as Andersen, 1986, suggests) and trading on this information is reflected in derivatives markets, one would expect these markets to be more sensitive to changes in informational flows, and therefore exhibit more volatile volume. Note that the median absolute change is lower than the mean for each of the volume series, suggesting that some days have very large positive changes in trading volume; this is confirmed by the consistently positive skewness statistic for each of the four series.

Figure 1 presents the time-series plots of the series. In this figure, the E-mini and legacy futures series are combined for convenience, taking into account the differences in the

[7] The multiplier for the S&P 500 legacy futures contract changed from 500 to 250 on November 3, 1997. Therefore, prior to this date, the legacy volume is multiplied by a factor of 2.

multipliers.[8] All series are highly volatile, thus confirming the patterns in Panel B of Table 1. The upward trend in the series is consistent with the strong increase in stock trading activity documented elsewhere (e.g., Chordia, Roll, and Subrahmanyam, 2011). Spider (ETF) volume has grown the most dramatically. It is worth noting that minimum transaction size restrictions are less onerous in the ETF market (as pointed out earlier, the S&P500 ETF trades in units of one-tenth of the index whereas the multiplying factor for legacy index futures is 250). This aspect possibly adds to the attractiveness of ETF markets for small investors and has contributed to the strong up-trend in conjunction with other innovations like online brokerage that have facilitated trading by small investors. Since the legacy and E-Mini series may possibly cater to different clienteles due to their differing contract sizes, we analyze the series separately for the remainder of the paper.

Table 2 provides the correlation matrices for levels (Panel A) and percentage changes (Panel B.) The legacy futures volume levels (Panel A) are negatively correlated with other volume series, presumably because legacy futures volume has trended downwards whereas the other series have trended upwards. The negative correlation pattern for futures disappears in Panel B, which reports correlations in percentage daily changes. Indeed, percentage changes in volume are strongly positively correlated amongst all of the series.

II. Time-Series Regularities

One of our primary goals is to analyze the joint dynamics of the time-series. For this exercise, the preferred method is a vector autoregression (VAR). In VAR estimation, it is desirable to first remove common regularities and trends from the time-series in order to mitigate the possibility of spurious conclusions. Series with secular trends, seasonal, or other common time-series regularities may seem to exhibit joint dynamics simply because of such commonalities. Prior research (Chordia, Roll, and Subrahmanyam, 2001) finds that market-wide bid-ask spreads do indeed exhibit time-trends and calendar seasonals. It seems quite possible that the volume series could also exhibit such phenomena.

[8] Thus, the futures series plotted is legacy futures volume + 0.2 * E-mini futures volume.

Thus, after log-transforming the raw volume series (to address the skewness documented in Table 1), we adjust them for deterministic variation; (see Gallant, Rossi, and Tauchen, 1992 for a similar approach to adjusting equity volume). Since little is known about seasonalities or regularities in contingent claims volume, this adjustment is of independent interest. In Section III, innovations (residuals) from the adjusted regressions are related with each other in a VAR.

The following variables are used to account for time-series regularities: (i) Four weekday dummies for Tuesday through Friday, (ii) 11 calendar month dummies for February through December, (iii) for the options and futures series, a dummy for the four days prior to expiration (the third Fridays in March, June, September, and December) to control for any maturity-related effects, (iv) Legendre polynomial fits (up to a quartic term) to account for any long-term trends. In addition to these variables, rebalancing trades by agents in response to major informational announcements (Kim and Verrecchia, 1991), and informed trading prior to such events, suggests dates surrounding macroeconomic releases might be unusual. We thus include indicator variables for macroeconomic announcements about GDP,[9] the unemployment rate, and the Consumer Price Index. We use a dummy variable for the five days preceding the macro announcement date and another for the announcement date and four days thereafter. Since announcements are generally made in the morning (Fleming and Remolona, 1999), the release date itself mostly belongs to the post-announcement period. The choices for dummies are based on prior evidence that trading activity and liquidity are altered before as well as after these announcements (Chordia, Sarkar, and Subrahmanyam, 2005).

Table 3 reports regressions of the natural logarithms of the five raw volume series on the preceding adjustment variables. We report the heteroskedasticity and autocorrelation-consistent (HAC) *t*-statistics computed as per Newey and West (1987).[10] Since there are a large number of

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[9] GDP numbers are released in three stages: advance, preliminary, and final. Our exploratory analysis revealed that trading activity only responds to the announcement of the preliminary number. Hence this is the announcement used to construct the dummy variable for GDP announcements.

[10] As suggested by Newey and West (1994), we use the lag-length to equal the integer portion of $4(T/100)^{(2/9)}$, where T is the number of observations. This indicates a lag length of eight in our case.

coefficients in Table 3, for parsimony, the following discussion is restricted to coefficients that are significant at the 5% level or better.

First, confirming the results observed in Figure 1, the linear trend term is strongly positive for the cash index, the options, the E-mini futures, and the ETF, but negative for the legacy futures. It is easily verified that this term also dominates the other polynomial terms and its coefficient conveys the sign of the overall trend in the series. The positive trend in futures volume evident within Figure 1 thus is due to the fact that the positive trend in E-mini volume dominates the negative trend in the legacy futures volume. Figure 2 depicts this phenomenon by plotting separately the legacy and E-mini contract volumes and clearly demonstrates that the E-mini contract has at least partially supplanted legacy futures volume. Note that the E-mini contract is electronically traded, whereas the legacy contract is traded via open outcry (Hasbrouck, 2003). The speed of execution offered by electronic markets (Barclay, Hendershott, and McCormick, 2003), together with the smaller contract size of E-mini futures, may have contributed to the rise of this contract's popularity vis-à-vis the legacy contract. Also note from Figure 2 that both futures series exhibit a number of spikes. Our examination of the dates of these spikes indicates that they do not correspond to any specific periods such as proximity to expiration dates. Since the spikes are not associated with any calendar regularities, we do not adjust the series further to account for the spikes.

We also note that the cash S&P 500 has a strong January seasonal in volume, which is not as evident in its contingent claims. This suggests that the January cash market volume increase is driven by individual stock trading activity, rather than by a common influence. Our finding is consistent with stock investment surges at the beginning of the calendar year due to cash inflows to some retail investors in the form of year-end bonuses (Ogden, 1990), and with re-investments following tax loss motivated selling just prior to the end of the previous year (Roll, 1983). Since these activities have no fundamental information content, the derivatives volume series do not respond as much.[11] We observe that volume in all series is statistically lower on

[11] The monthly coefficients for options are mostly negative for February through December, though four are not significant. As a group, they also indicate a larger volume in January but the effect is statistically smaller than in the cash (spot) market.

Mondays relative to other days of the week. This is a result with no obvious explanation, and deserves analysis in future research. It may be worthwhile to investigate whether this regularity is also found in contingent claims on other assets such as bonds and foreign currencies, and if so, to uncover the underlying cause.

Cash and contingent claims volumes generally tend to be higher on days surrounding unemployment and CPI announcements (legacy futures volume tends to be higher around GDP announcements). Due to the use of logarithms, the regression coefficients have the usual proportional change interpretation; thus, for example, the coefficients imply that cash index and options volumes are higher by 6% and 5%, respectively, in the period subsequent to the unemployment release. These findings indicate that traders adjust their holdings in response to the new macroeconomic information conveyed by the announcement (Kim and Verrecchia, 1991). We also find that futures and options volumes are significantly higher just prior to contract expiration, likely due to the closing out of positions just prior to expiration (Stoll and Whaley, 1990).

III. Joint Dynamics of Contingent Claims Volume

The regressions of the previous section yield five OLS residual series whose dynamics we now analyze with a vector autoregression (VAR). A VAR seems desirable because the five volumes are likely to be jointly determined. For example, informed agents are likely to trade in contingent claims due to lower transaction costs, and their trades are likely to be followed by others in the cash market.[12] Further, asset allocation trades between equities and bonds as a reaction to new public information may be conducted in cash markets as well as with contingent claims. This could result in the five volume series being cross-correlated, and to innovations in some series leading others.

To address such possibilities, a VAR is the natural tool. In this VAR, the five volume time-series OLS residuals described above are the endogenous variables. We test for stationarity

[12] See Chakravarty, Gulen, and Mayhew (2004) and Hirshleifer, Subrahmanyam, and Titman (1994).

of these residual series using an augmented Dickey-Fuller test. The existence of a unit root is rejected with a *p*-value of less than 5% in each of the five cases. Since volatility is a strong driver of volume (e.g., Gallant, Rossi, and Tauchen, 1991), a measure of anticipated volatility is included as an exogenous variable. The volatility measure is the VIX, an indicator of the implied volatility of the S&P 500 index published by the Chicago Board Options Exchange.[13] We use implied option volatility because speculative activity that sparks turnover would likely respond to expected volatility, rather than realized volatility.[14] In applying the VAR, the number of lags is determined by the Akaike and Schwarz information criteria. When these criteria indicate different lag lengths, the lesser lag length is chosen for the sake of parsimony. Typically, the slopes of the information criteria as a function of lag length are quite flat for longer lags, so the choice of shorter lag lengths is further justified. The criteria indicate a lag length of three for the VAR.

Correlations in VAR innovations are reported in Panel A of Table 4. The correlation patterns generally confirm those in Table 2; specifically, all series are strongly and positively cross-correlated. The correlation between the cash market and the E-Mini contract is the largest amongst all of the numbers reported in the table, perhaps indicating that both of these markets, with lower minimum transaction size requirements (as discussed in the previous section) attract a common clientele of small investors. The lowest correlation is between options and the legacy futures contract. Overall, these findings indicate that the volume series are jointly determined.

Panel B of Table 4 presents the coefficients of the exogenous proxy for volatility, i.e., VIX. All volumes are significantly and positively related to VIX. This supports the notion that higher expected future volatility is associated with increased volume, consistent with the results of Gallant, Rossi, and Tauchen (1991). The results also accord with the intuition that high expected volatility would increase returns from speculative trading (Kyle, 1985) and thus attract more informed volume.

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[13] The results are not qualitatively altered in the absence of VIX as an exogenous variable.

[14] We are grateful to Bob Whaley for providing the VIX data.

. In Panel C, we present Granger causality tests for whether the volume series are useful in forecasting shifts in each other (in a bivariate sense). We present chi-squared statistics and p-values for whether one series Granger-causes another, and a summary statistic for whether all other series are useful for forecasting shifts in a particular series. The results generally support joint determination. Thus, the cash series Granger-causes all of the contingent claims series, and the E-Mini and ETF series Granger-cause three of the four series. In every case, the combined chi-squared statistic is highly significant, indicating that cross-lags of other series provide significant forecasting power for each of the volume series.

As an alternative way of characterizing volume dynamics, Panel D of Table 4 shows the variance decompositions of the forecast errors for the VAR. Computations of these quantities is a standard exercise for a VAR (analytics appear in the Appendix). The decompositions convey insight on the information contributed by innovations in each variable contributes to the other variables (Hamilton, 1994). Specifically, they indicate the proportion of the error variance of a variable's forecast explained by shocks to each of the other variables. For brevity, we present results for a forecast horizon of ten days (the results are stable at lags between five and fifteen). Results from variance decompositions are generally sensitive to the specific Cholesky ordering of the endogenous variables.[15] In particular, placing a variable earlier in the ordering tends to increase its impact on the variables that follow it. Thus, we consider two illustrative orderings.

Our first ordering is options, legacy futures, E-Mini futures, ETF, and cash. We see from Panel D that the fraction of the error variance in forecasting options volume, due to innovations in options volume, is more than 95%. The corresponding number for legacy futures is 88%, but is less than 50% for the other three claims. Options and futures explain at least 10% and on occasion more than 30% of the error variances for the other contracts. However, the fraction of cross-error variances explained by the ETF and the cash markets are quite small. The next ordering places cash first, and leaves the rest of the ordering unchanged. In this case, the impact of options decreases dramatically, but the impact of cash increases considerably. We have verified that other orderings lead to similar conclusions; the variable placed first dominates the

[15] However, Granger causality tests are unaffected by the ordering of variables.

others in explaining forecast error variances. Note that in the orderings we present, whether cash volume is placed first or last, it continues to explain a reasonable portion of the forecast error variances of the other variables, suggesting joint determination. Indeed, in unreported analyses the forecast standard errors monotonically increase over time (i.e., are greater at longer forecast horizons), also indicating the existence of dynamic structure in the data

We now consider impulse response functions (IRFs), which portray the full dynamics of a VAR system. An IRF tracks the effect of a one standard deviation shock to one variable (henceforth termed a ”shock” or “innovation” for convenience) on the current and future values of the other variables. The appendix presents the analytics of impulse response functions in a VAR system. The standard method of performing IRF analysis is to use orthogonalized Cholesky decompositions (Sims, 1980), but these are also potentially sensitive to the ordering of variables. In our case, since Panel D of Table 4 indicates that ordering does matter, we consider generalized impulse response functions developed by Pesaran and Shin (1998), which are insensitive to the ordering of variables.[16]

Figure 3 shows the response of each volume to a unit standard deviation shock in the other volumes traced forward over a period of ten days. Monte Carlo two-standard-error bands (based on 1000 replications) are provided to gauge the statistical significance of the responses. Period 1 in the IRFs represents the contemporaneous response, whereas subsequent periods represent lagged responses. The vertical axes are scaled to the measurement units of the responding variable. We note from the figure that the auto-responses are strong and persistent for all derivative volumes and for cash volume. In each case, an initial volume shock for a variable is followed by significant volume in the same variable for at least ten days. The cross-responses in general are less significant. However, innovations in all the variables are remarkably consistent and significant in forecasting innovations in every other variable. The

[16] In general, innovations to a VAR may be cross-correlated, which make it infeasible to shock one variable without a specific method that addresses how the other innovations are affected. Cholesky responses suggested by Sims (1980) are to orthogonalized impulses in one variable, but in this case, the ordering of variables matters. Pesaran and Shin’s (1988) generalized responses are invariant to ordering. They involve impulses to one variable at a time, and the effect of the other error terms are integrated out, assuming normality of the residuals (see Pesaran and Shin, 1988, and Warne, 2008). The qualitative results on joint dynamics in our case are largely invariant to whether Cholesky innovations are used.

responses are economically significant; for example, the response of cash volume to a one-standard-deviation innovation in options volume cumulates to 0.2 standard deviation units over ten days, and the other responses are generally of a similar order of magnitude. Thus, the IRFs as well as the variance decompositions are consistent with joint determination of the volume series.

IV. Volume and Price Formation

The volume series are worth examining in their own right, but we now turn to their link with macroeconomic states. If it is costly to obtain timely data on volume, then volume is not public information, and return predictability based on volume would not violate semi-strong market efficiency (Grossman and Stiglitz, 1980). Note, however, that by its very nature, total volume does not reveal whether the trade is initiated by a buyer or a seller, which presumably limits the ability of volume to predict signed returns. Nonetheless, if volume represents trading on information, then it could predict absolute returns, especially around informational announcements, because high absolute returns would signify a strong informational signal and thus higher volume prior to the announcement. More specifically, if futures and options trading can be used to get around cumbersome short-sales constraints in the cash market and thus enable more effective trading on information, high volume in contingent claims prior to informational announcements may predict absolute returns following the announcement. Further, since options cover more contingencies than other (linear) derivatives, volume in options markets may play a more material role in forecasting movements in macroeconomic variables than trading activity in other contingent claims.

We perform the analysis in two different ways. We first take a look at the empirical relation between cash and contingent claims volume, and daily shifts in common macroeconomic indicators.[17] We then explore the behavior of volume around major announcements to ascertain

[17] We use the unadjusted volume series, rather than the residual series used for the VAR, because the residual series suffers from a look-ahead bias (the full time-series is used to construct the residuals), thus hampering the interpretation of predictability results.

the predictive ability of different volume series for price formation around the release of material macroeconomic data.

A. Volume and the Macroeconomy

We consider four macroeconomic variables; the term spread, the credit (or default) spread, the short-term interest rate, and the return on a broad stock market index. Here, the short-term interest rate is represented by the yield on three-month Treasury Bills. The term spread is the difference in yields between Treasury bonds with more than ten years to maturity and Treasury Bills that mature in three months. The credit spread is the yield differential between bonds rated Baa and Aaa by Moody's.[18] The S&P 500 is the broad stock market index. While other variables could also be proposed, these variables have been used by Ferson and Harvey (1991), among others, and their advantage is that they are available on a daily basis that matches the interval of the volume series. The use of daily data, of course, promises better power in testing the predictive ability of volume for shifts in macroeconomic indicators.

Panel A of Table 5 presents summary statistics (means and standard deviations) plus daily contemporaneous correlation matrix between the logged volume series and the absolute values of the first differences in the macroeconomic variables, as well as the absolute value of the S&P 500 return. We find that with the exception of legacy futures and the credit spread, the correlations of all of the volume series with unsigned shifts in macro variables are positive. The highest correlations are observed between the options volume and the macroeconomic variables. ETF volume also shows high correlations with the term spread as well as the credit spread, and cash volume is highly correlated with the term spread. Though the positive correlations suggest that volume and macroeconomic indicators are related, they do not directly show that volume conveys information about the macroeconomy; we turn to this issue next.

Table 5 also presents *predictive* regressions (Panel B) where the dependent variables are the absolute values of the first differences in the macroeconomic variables, and the absolute

[18] The (constant maturity) data on the interest rate variables are obtained from the Federal Reserve website at the URL http://www.federalreserve.gov/releases/h15/data.htm#fn11.

value of the S&P 500 return.[19] The right-hand volume variables represent the sum of the natural logarithms of volumes on the three lags of each of the five volume series. In addition, we control for the average three-day lag of the dependent variable (labeled "LagDepVar"). Again, as in Table 3, we use the Newey and West (1987) method to adjust the standard errors of the coefficients. Note that the absolute return on the index is a measure of realized and more likely to be determined as a consequence of trading activity, as opposed to VIX, which is traders' expectations of volatility, and is therefore more likely to cause trading activity. This argument justifies using the absolute return as a dependent variable in Panel B of Table 5.

We find that option volume positively predicts non-signed shifts in three of the four macroeconomic variables (the *p*-value for the 4th variable, the short rate, is 0.106). Since the right-hand variables are expressed in natural logarithms, the coefficients can be interpreted in terms of proportional change in the independent variable. Thus, a options volume shift in the amount of the mean daily options volume shift change documented in Table 1 (i.e., 0.38) is associated with an extra 0.08% shift in the term spread. We also find that cash volume positively predicts absolute shifts in the short rate. Legacy futures volume is positively related to future absolute movements in the short-rate, the term spread and the stock market. E-mini futures have significant negative predictive ability for two of the four macro variables. However, the bivariate correlations between the dependent variables and E-mini futures volume are positive in every case. The negative coefficients on E-Mini volume arise because of a high cross-correlation (0.9) between E-mini volume and ETF volume, which leads to multicollinearity in the right-hand variables.[20] The adjusted R^2's range from 33% for the short rate to 14% for the credit spread.

Note also that absolute equity returns (a measure of volatility) are predictable not only from their own lagged values but additionally from volume in contingent claims. Indeed, increases in options, legacy futures, and ETF volumes all strongly predict upward shifts in stock market volatility after controlling for past volatility. The positive relation between volume and

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[19] Using signed shifts in macroeconomic variables as dependent variables (i.e., using signed as opposed to absolute changes in the context of Table 5) yields no significance for the volume variables; we therefore omit these regressions for brevity. We revisit this issue in the next section.

[20] None of the other correlations between contingent claims volume series exceed 0.9.

volatility accords with Karpoff (1987), who demonstrates such a link for cash equities. Our findings underscores the role of *contingent claims* volume in cash market volatility.

The overarching message of this subsection is the reliable evidence that volume series contain information about absolute shifts in the macroeconomic variables, including stock market volatility, with the option and legacy futures markets playing a particularly material role. Note that predicting absolute returns with unsigned volume does not allow the disentanglement of speculative versus hedging activity; this is best done with signed volume proxies, an exercise taken up in Section V.

B. Predictive Role of Volume Around Macroeconomic Announcements

Fleming and Remolona (1999) as well as Chordia, Roll, and Subrahmanyam (2001) suggest that GDP, CPI, and unemployment announcements influence equity market liquidity, indicating information-based trading prior to these announcements. Based on these findings, one would expect volume (which partially reflects information-based trading) to affect price formation around these announcements. We thus consider whether trading activity in the contingent claims predicts absolute returns on the day of the macroeconomic news releases. By simultaneously including volume on several contingent claims, we are able to shed light on the relative roles of various contingent claims and the stock market in price formation around macroeconomic news releases.

We first collect information on the date of release of these announcements throughout the sample period. We then perform a predictive regression in which the dependent variable is the absolute value of the return on the S&P 500 index on the day of the macroeconomic announcements. This variable is regressed on the sum of logged volumes on the three days preceding the announcement for each of the volume series.[21] In addition, controls are included for the average absolute return over the past three days.

[21] Including additional lags (up to ten) makes no material difference to the results; these additional lags are insignificant.

We find that options volume significantly predicts absolute returns on the day of the unemployment and Consumer Price Index announcements, and this result is consistent with the significance of this variable in Table 5.[22] We also find that legacy futures volume significantly forecasts absolute returns on the day of the GDP announcement. The other coefficients are insignificant, except for the forecasting ability of the absolute cash return for the absolute return on the day of the CPI announcement. The adjusted R^2 ranges from a surprisingly high 14% for the CPI regressions to less than 5% for the other two. The forecasting ability of trading activity in options markets for absolute returns on the day of two of the three macroeconomic news releases supports the notion that the nonlinear payoffs afforded by options make them particularly appealing to speculators and hedgers relative to other claims; we will shed further light on this issue in the next section.

V. Imputed Signed Volume

In this section we consider imputed signed volume, as opposed to using unsigned volume. The rationale is that signed volume may bear a stronger relation to signed changes in the macroeconomic variables, because it may convey privately informed traders' buying and selling activities, as pointed out by Chordia, Roll, and Subrahmanyam (2002). We proxy for signed volume in the spirit of Pastor and Stambaugh (2003), who consider the sign of the return on a day times volume on that day as a proxy for signed volume. We follow their procedure for ETF volume. The other series are obtained as follows. First, the S&P 500 signed volume is obtained by multiplying the value-weighted volume on the S&P 500 by the sign of the return on the S&P 500 index. For options, we multiply contract volume (as used in the previous section) by the sign of the price change in each contract (reversing the sign for puts), and then aggregate across contracts to get signed volume. Imputed signed futures volume is obtained in the same way. We do realize that these series measure signed volume with error; however, note that this would make any predictive relation using these series even more striking.

[22] Again, the coefficients can be interpreted in terms of proportional changes in the volume variable; thus, the coefficient of 1.72 for options volume in the case of unemployment announcements implies that a shift in options volume equal to the mean options volume shift of 0.38 in Table 1 implies an extra absolute return of 0.07%. We leave it for the reader to perform other such illustrative calculations on economic significance.

We first consider the version of Table 6 where the original volume series are replaced with their signed counterparts, and the dependent variable is replaced with the signed return. This allows us to examine whether imputed signed volume in contingent claims predicts returns on the day of important macroeconomic announcements. Note that the signing introduces negative numbers in roughly half the observations, so we cannot use logarithms as in Table 6. Thus, we use the raw versions of the variables but transform them to units of their standard deviation to make the coefficients readable.[23] The results appear in Table 7.

Overall, the evidence accords with a market that is quite efficient, in that the predictive power of most of the variables for announcement-day returns does not approach significance. However, consistent with the results for absolute returns in Table 6, we find that options activity prior to unemployment and CPI announcements forecasts signed returns on the day of the announcements. The adjusted R^2's, at 3% and 4%, respectively, for the two regressions, are reasonable for signed returns. The findings imply that bullish options activity predicts lower returns on the day of the announcement. Thus, the results, though reliably significant, do not provide evidence of speculative activity as that would imply the opposite sign on the coefficients. On the other hand, the results suggest that agents hedge themselves prior to material macroeconomic announcements. Thus, the negative coefficient on options volume is consistent with the notion that prior to a large negative return, agents buy calls or sell puts to protect themselves against losses in an underlying diversified portfolio of equities. This finding accords with Easley, O'Hara, and Srinivas (1998), who also find that individual stock returns are negatively associated with lags of signed options volume; they also attribute this result to hedging. Similarly, the analysis of Schlag and Stoll (2005) in a German context indicates that lagged index option volume negatively predicts relative changes in DAX futures prices. Schlag and Stoll (2005) also find that signed futures volume does not predict DAX futures returns but, as observed above, signed options volume does. In our context, the only other signed volume series that has predictive power for returns is cash volume for GDP announcements but the adjusted R^2 of that regression is negligible.

[23] An alternative specification where the variables are transformed by adding a shift parameter equal to constant equal to 1.0 plus the negative of the minimum of every series, and then natural-logged, leads to similar results for the analyses of this section.

Next, we investigate how imputed signed volume relates to day-to-day shifts in variables that measure the aggregate macroeconomy. Thus, we use the five signed volume series in a vector autoregression that includes signed S&P 500 returns and first differences in the short rate, as well as the term and credit spreads (i.e., the signed versions of the macroeconomic series used in Table 5),[24] and VIX as an exogenous variable. These raw series show no evidence of non-stationarity as per an augmented Dickey-Fuller test, so we do not adjust them prior to their usage in the VAR.[25] Since there are many variables (one exogenous variable and nine endogenous ones) in the VAR, to be succinct, we report selected results. All these results emanate from the full VAR specification.

Panel A of Table 8 presents the correlations in VAR innovations between the signed volume series and the macroeconomic variables. The volume series innovations are positively correlated with those in all the macro variables except the credit spread. The correlations are highest with the S&P 500 return, and lowest with the term spread. Options volume innovations have a high correlation (exceeding 0.6) with innovations in cash returns, and also have the highest correlation with innovations in the short rate. Interestingly, imputed signed volume is negatively associated with shifts in the credit spread, though the sizes of the correlations are modest.

In Panel B, we present Granger causality tests for whether the imputed signed volume series are useful in forecasting signed shifts in the macroeconomic variables (in a bivariate sense) after controlling for own-lags and lags of all of the other variables in the complete VAR. The results indicate that signed options volume is useful in forecasting all of the series at a *p*-value of

[24] The results are not sensitive to whether an additional return proxy, the return on the exchange-traded fund, is included in the VAR.

[25] While including lagged returns in the VAR (by definition) partially addresses the concern of slow adjustment of the index to new information due to non-synchronous trading, we perform an additional check by adopting the approach of Jokivuolle (1995). He devises a method for adjusting index returns for stale prices by showing that the true index level can be represented as the permanent component of a Beveridge and Nelson (BN) (1981) decomposition of the observed log index series. To apply this method to our S&P 500 return series, we first compute the observed stock index level by normalizing the index at the beginning of the sample period to 100 and then updating it based on observed returns. We then extract the BN permanent component for the seriies. Finally, we use returns implied by the BN-adjusted index in place of the original S&P 500 returns in the VAR. Results are qualitatively unaltered using these adjusted returns; full details are available upon request from the authors.

less than 0.1. Specifically, innovations in imputed signed options volume are useful in forecasting those in the S&P 500 return and shifts in the short rate at the 10% level, and those in the term spread and the credit spread at the 5% level of significance. Legacy futures and ETF volume innovations are material only in forecasting those in the stock market return and the short rate, at the 5% and 10% levels, respectively, and ETF volume is material only in forecasting shifts in the short rate. All other Granger causality results are insignificant. Thus, overall, the evidence in Panel B points to options markets as the dominant vehicle in forecasting the macroeconomic environment.

Figure 4 presents the generalized impulse responses of the macroeconomic variables to shocks in imputed signed volume. These responses, which, as observed earlier, account for the full dynamics of the VAR system, indicate that signed option volume innovations are useful in forecasting all of the macroeconomic series. Negative innovations to signed option volume indicate a future decrease in the short rate, and portend increases in the term and credit spreads. Since an increase in the credit and term spreads implies an increase in risk premia on long-term assets, and an increase in short rates (*ceteris paribus*) signifies a decrease in risk premia,[26] the results suggest that bearish volume in the options market portends a decline in the macroeconomic environment.[27] Thus, the IRFs are consistent with speculative activity in options markets that predicts the state of the macroeconomy. There also is a modest forecasting relation between signed option volume and future S&P 500 returns.[28] Note that the responses involving the other contingent claims volume series either are not consistently significant across all macroeconomic variables, or are less persistent than those in the options market.

[26] See, for example, Jamk (2011). At longer horizons, of course, there is well-known evidence that an inverted yield curve is associated with future recessions (Harvey, 1986), because it signals the future interest-rate lowering stance of the Federal Reserve to combat a recession. However, we do not have enough power to test whether trading activity forecasts long-lived recessions within our sample period of less than fourteen years.

[27] The graphs are in standard deviation units. The responses exhibit modest economic significance; for example, the unreported summary statistics imply a cumulative short rate and term spread responses of about 0.02 standard deviation units (about one-tenth of one percent) to a one-standard-deviation innovation in signed option volume. The other responses are of the same order of magnitude.

[28] The cumulative response of the S&P 500 return to an options volume innovation is positive, which is consistent with the notion that bearish options volume forecasts a deterioration in the macroeconomic environment and thus forecasts a downward move in stock prices.

Taken in totality, the results suggest that the options market is dominant over the other volume series with regard to forecasting shifts in the macroeconomic environment. Thus, options markets, which offer non-linear exposures and higher leverage, stimulate the most informative speculative activity relative to other contingent claims.

VI. Conclusion

Trading is a costly activity, and is known to influence financial market liquidity and required returns (Branch and Freed, 1977; Datar, Naik, and Radcliffe, 1998; and Amihud and Mendelson, 1986), so it is worthwhile to examine the dynamics of trading activity. While trading in equities is well-studied (e.g., Gallant, Rossi, and Tauchen, 1992), it is far less so in contingent claims. Indeed, the finance textbooks that we use as a profession exposit well how contingent claims should be priced relative to cash assets;[29] but because of a lack of research on the issue, are silent on the relative extent of volume in these claims.

To the best of our knowledge, this paper contains the first analysis of the joint time-series of the trading activity in the cash equity market and its contingent claims. We study the dynamics of trading volume in the cash S&P 500 index and its four derivatives: index options, index futures (both the legacy and the E-mini contracts), and the ETF. This provides some empirical information about the degree to which trading activity in contingent claims is jointly determined and the extent to which the various contingent claims play a role in price formation *relative* to each other. The data used here span a long time-period of twelve years (more than 3000 trading days), thereby providing some assurance of reliability. We are not aware of another study that has analyzed the joint time-series of trading activity in multiple contingent claims and on the underlying asset over such a long time-period.

We find that the volumes on S&P index options, the ETF, the E-mini futures and on the cash index itself have trended upward over recent years but legacy futures volume has trended downward. The overall index futures volume (legacy plus E-mini) has trended upward,

[29] E.g., Bodie, Kane, and Marcus (2009), Chapters 21 to 23.

indicating that the E-mini has at least partially supplanted the legacy contract, owing possibly to its smaller contract size and electronic trading protocol. Calendar regularities also differ across contracts; for example, there is a January volume seasonal in the cash index but this is not as strongly evident in its contingent claims, which reveals trading in individual stocks at the turn of the year.

Vector autoregressions indicate that the time-series are jointly determined. First, the series are strongly cross-correlated, and impulse responses indicate that all series provide useful information in forecasting each other. Options volume (signed as well as unsigned) predicts shifts in the credit spread, term spread, and the market index. Furthermore, volumes in options and legacy futures forecast stock market volatility even after accounting for volatility persistence. Options volume also predicts absolute returns on the day of major macroeconomic announcements, suggesting that agents trade on private information in derivative markets, possibly to circumvent short-selling constraints in cash markets. The general picture that emerges from the analysis is that options markets, with enhanced leverage and nonlinear payoffs that cover more contingencies relative to other contingent claims, play the most material role in forecasting the macroeconomic environment amongst all of the contingent claims on the stock market.

This study is necessarily empirical in nature because there are virtually no models of trading across multiple contingent claims on the same underlying asset. Our study in fact underscores the importance of developing explicit theoretical models that incorporate trading in multiple contingent claims. Much more needs to be done on the empirical side as well. For example, relating how these series contribute to price formation around other announcements, such as shifts in the stance of the Federal Reserve, would be intriguing. Further, an investigation into what types of clientele (individuals versus institutions) these different markets attract would also be of considerable interest. Finally, the joint analysis of the time-series of multiple contingent claims in other markets (e.g., bonds, foreign exchange, and commodities) remains an un-addressed issue. These issues form a fertile agenda for future research.

Appendix

This appendix presents the algebra for impulse response functions and variance decompositions. A p 'th order vector autoregression can be written as

$$y_t = c + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \ldots + \Phi_p y_{t-p} + \varepsilon_t,$$

where ε_t is white noise. Assuming the processes are covariance stationary and y has an ex ante mean of μ, the VAR has a VMA representation:

$$y_t = \mu + \varepsilon_t + \Psi_1 \varepsilon_{t-1} + \Psi_1 \varepsilon_{t-1} + \ldots \equiv \mu + \Psi(L)\varepsilon_t.$$

Thus, the matrix ψ has the representation

$$\partial y_{t+s} / \partial \varepsilon_{t'} = \Psi_s,$$

which is the impulse response vector. A plot of the row i, column j element of Ψ_s:

$$\partial y_{i,t+s} / \partial \varepsilon_{jt}$$

as a function of s is called the impulse response function (IRF). Thus, the IRF measures the cumulative impact of a unit innovation in one variable on future shifts in the other variables, while accounting for the full dynamics of the VAR. In other words, a significant IRF indicates that innovations in one variable are useful in forecasting shifts in the other. Let Ω represent the variance-covariance matrix of the ε's. Then there exist vectors A and matrices D such that

$$\Omega = AD^{1/2}D^{1/2}A' \equiv PP'$$

where $P \equiv AD^{1/2}$. Defining $v_t \equiv P^{-1}\varepsilon_t$, one can instead calculate the Cholesky decomposed impulse response functions

$$\partial y_{i,t+s} / \partial v_{jt} = \Psi_s.$$

The generalized impulse responses for a shock δ_j to ε_{jt} are

$$GI_y(\delta_j) = E(y_{t+h} \mid \varepsilon_{jt} = \delta_j, I_{t-1}) - E(y_{t+h} \mid I_{t-1}).$$

If we assume that $\delta_j = \sigma_{jj}$, the standard deviation of ε_{jt}, then it is shown by Pesaran and Shin (1998) that

$$GI_x = \Psi_h \Omega e_j \sigma_{jj}^{-1/2},$$

where e_j is a vector of zeroes save one as its j 'th element.

Now, the mean-squared error of the s-period ahead forecast is

$$\Omega + \Psi_1 \Omega \Psi_{1'} + \Psi_2 \Omega \Psi_{2'} + \ldots + \Psi_{s-1} \Omega \Psi_{s-1}'.$$

Since we can write $\varepsilon_t = Au_t$,

$$\Omega = E(\varepsilon_t \varepsilon_{t'}) = a_1 a_{1'} \cdot \mathrm{v}ar(u_{1t}) + a_2 a_{2'} \cdot \mathrm{v}ar(u_{2t}) + \ldots + a_n a_{n'} \cdot \mathrm{v}ar(u_{nt}).$$

The mean-squared error then becomes

$$MSE(\hat{y}_{t+s} \mid t) = \sum_{j=1}^{n} \left\{ \mathrm{v}ar(u_{jt}) \cdot \left[a_j a_{j'} + \Psi_1 a_j a_{j'} \Psi_{1'} + \Psi_2 a_j a_{j'} \Psi_{2'} + \ldots + \Psi_{s-1} a_j a_{j'} \Psi_{s-1}' \right] \right\}.$$

The contribution of the j'th innovation to the forecast error is simply

$$\mathrm{v}ar(u_{jt}) \cdot \left[a_j a_{j'} + \Psi_1 a_j a_{j'} \Psi_{1'} + \Psi_2 a_j a_{j'} \Psi_{2'} + \ldots + \Psi_{s-1} a_j a_{j'} \Psi_{s-1}' \right].$$

Alternatively, in terms of the Cholesky decomposition, we know that $a_j \cdot \mathrm{s}td(u_{jt})$ is equal to p_j, the j'th column of P and so we can express the MSE also as

$$MSE(\hat{y}_{t+s} \mid t) = \sum_{j=1}^{n} \left[p_j p_{j'} + \Psi_1 p_j p_{j'} \Psi_{1'} + \Psi_2 p_j p_{j'} \Psi_{2'} + \ldots + \Psi_{s-1} p_j p_{j'} \Psi_{s-1}' \right],$$

with the contribution of the j'th innovation being

$$p_j p_{j'} + \Psi_1 p_j p_{j'} \Psi_{1'} + \Psi_2 p_j p_{j'} \Psi_{2'} + \ldots + \Psi_{s-1} p_j p_{j'} \Psi_{s-1}'.$$

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Table 1: Summary statistics

Here are summary statistics for daily volume on the S&P 500 index (Cash), and on S&P 500 options, legacy futures, E-Mini futures, and the "Spider" ETF (SPDR). In Panel A, the means, medians, standard deviations, and mean absolute deviations are in millions of contracts (futures, legacy and E-Mini), dollar volume (options) or shares (ETF and Cash). SPDRs trade in units of one-tenth of the index, legacy futures trade in units of 250 times the index and E-Mini futures trade in units of 50 times the index. Panel B presents summary statistics for daily absolute changes in percentages. The time-period is September 1997 (debut of the E-Mini contract) through December 2009.

Panel A: Levels

Statistic	Cash	Options	Futures	E-Mini	ETF
Observations	3526	3524	3342	3097	3525
Mean	58.36	5.48	74.6	836.04	71.08
Median	49.74	2.59	62.56	609.53	32.49
Standard deviation	34.64	7.89	52.12	920.45	106.61
Mean absolute deviation	26.23	4.89	39.01	690.95	72.56
Skewness	1.32	3.93	1.53	1.64	2.53
Kurtosis	2.17	23.15	2.59	3.21	7.69

Panel B: Daily absolute changes (in percentages)

Statistic	Cash	Options	Futures	E-Mini	ETF
Observations	3525	3523	3341	3095	3523
Mean	13.3	38.0	23.5	21.2	31.0
Median	9.72	29.8	17.9	16.2	24.1
Standard deviation	14.3	33.7	22.0	21.6	29.5
Mean absolute deviation	9.23	24.8	15.7	14.3	20.3
Skewness	3.34	1.89	2.21	3.09	4.14
Kurtosis	17.1	5.60	7.51	16.1	45.9

Table 2: Correlation matrix

Here are correlation matrices for daily volume in the S&P 500 (cash) Index, and S&P 500 options, futures (legacy and E-Mini), and ETF. The time-period is September 1997 through December 2009.

Panel A: Levels

Variable	Cash	Options	Futures	E-Mini
Options	0.772			
Futures	-0.184	-0.061		
E-Mini	0.873	0.829	-0.137	
ETF	0.847	0.886	-0.170	0.946

Panel B: Daily Percentage Changes

Variable	Cash	Options	Futures	E-Mini
Options	0.442			
Futures	0.557	0.375		
E-Mini	0.726	0.431	0.702	
ETF	0.549	0.317	0.522	0.653

Table 3: Time-Series Regressions of Volume

Log Volume in the S&P 500 (cash) Index and in S&P 500 Options, Futures (legacy and E-Mini contracts), and "Spider" ETF are regressed on variables intended to remove calendar regularities and trends. Four Legendre polynomials of time, linear through quartic, measure secular non-linear trends. Day-of-Week and Month dummies account for seasonals. Macroeconomic announcements are for Unemployment, the CPI, and the main GDP announcement (not the advance announcement.) The macroeconomic dummies are turned on for two five-day periods: (1) on the five days preceding the announcement and (2) on the announcement date plus the four following days. The Remtrm dummy for options and futures is unity for the four days prior to expiration of the contracts (the third Fridays in March, June, September, and December). The time-period is September 1997 through December 2009. The Newey and West (1987) method with eight lags corrects the standard errors for heteroskedasticity and autocorrelation in the OLS residuals.

Body of Table is on following page.

Explanatory Variable	Cash		Options		Legacy Futures		E-Mini Futures		ETF	
	Coeff.	T-Stat.	Coeff.	T-Stat.	Coeff.	T-Stat.	Coeff.	T-Stat.	Coeff.	T-Stat.
Linear	0.6595	43.44	1.1379	34.37	-0.6628	-20.80	2.6845	107.65	2.2421	59.12
Quadratic	0.1375	7.84	0.7945	19.77	-0.0179	-0.43	-0.9229	-27.29	0.0151	0.32
Cubic	0.1639	7.59	-0.0484	-0.97	0.0364	0.72	0.2306	5.76	-0.1174	-2.05
Quartic	-0.5207	-19.53	-0.5520	-9.66	-0.2248	-3.95	0.1325	2.79	0.0371	0.58
Tuesday	0.0898	12.31	0.1728	7.59	0.1582	11.90	0.1271	9.16	0.1439	7.59
Wednesday	0.1207	14.97	0.1892	8.13	0.2012	13.28	0.1700	12.43	0.1799	9.16
Thursday	0.1244	12.16	0.2516	9.75	0.2979	13.30	0.1904	10.64	0.2086	8.58
Friday	0.0627	5.51	0.0993	3.59	0.2185	9.85	0.0804	4.04	0.1464	6.34
February	-0.0965	-2.85	-0.1871	-2.52	-0.0154	-0.29	-0.0611	-1.08	-0.0101	-0.11
March	-0.0691	-2.01	0.0020	0.03	0.3758	4.28	0.0395	0.65	0.1054	1.21
April	-0.0700	-2.16	-0.1042	-1.41	-0.0606	-1.09	-0.0114	-0.22	0.0526	0.66
May	-0.1497	-4.90	-0.1892	-2.86	-0.0661	-1.35	-0.0794	-1.49	-0.0424	-0.54
June	-0.1546	-4.40	-0.1957	-2.46	0.3576	4.12	-0.0287	-0.47	-0.0290	-0.35
July	-0.1345	-3.35	-0.1834	-2.00	-0.1031	-1.58	-0.0450	-0.64	-0.0260	-0.25
August	-0.2471	-6.38	-0.1922	-1.97	-0.0822	-1.26	-0.1394	-2.01	-0.0455	-0.42
September	-0.1068	-2.61	-0.0061	-0.07	0.4075	4.81	0.0334	0.52	0.0402	0.37
October	-0.0520	-1.39	0.0457	0.48	0.0080	0.12	0.0591	0.90	0.1560	1.55
November	-0.1510	-4.23	-0.1235	-1.30	-0.0475	-0.86	-0.1290	-1.95	-0.0555	-0.57
December	-0.2424	-5.45	-0.2158	-2.53	0.2073	2.01	-0.3801	-4.62	-0.2477	-2.71
Unem-5-1	0.0332	2.02	0.0863	2.09	0.3232	7.72	0.1121	3.64	0.0344	0.92
Unem 0+4	0.0626	4.24	0.0492	1.55	0.2134	6.67	0.1104	4.13	0.0938	2.90
CPI -5-1	0.1016	6.50	0.2032	5.81	0.0205	0.61	0.0765	2.94	0.0671	2.11
CPI 0+4	0.0645	4.15	0.2470	6.79	0.2052	5.47	0.1365	5.06	0.1102	3.23
GDP2-5-1	-0.0456	-1.34	-0.0389	-0.58	0.2733	5.10	-0.0334	-0.64	-0.0122	-0.20
GDP2 0+4	0.0028	0.14	-0.0339	-0.60	0.3866	9.08	0.1000	2.31	0.0649	1.06
RemTrm			0.1824	3.54	0.8448	14.51	0.1569	3.62		
Intercept	17.856	601.69	14.971	225.63	10.502	220.54	12.596	251.72	17.169	238.08
Adjusted R^2	0.8192		0.7044		0.5722		0.9515		0.8768	

Table 4: Selected VAR Results

Correlations in the innovations from a vector autoregression (Panel A) coefficients on the exogenous variable, VIX, (Panel B), Granger causality results (Panel C), and variance decompositions (Panel D) are reported for daily OLS residuals obtained by regressing the natural logarithms of trading volume of the S&P 500 Index, and of S&P 500 options, futures, and the ETF against calendar regularities and macroeconomic announcements, as shown in Table 3. The time-period is September 1997 to December 2009. Volume is in number of contracts. The coefficients in Panel B are multiplied by 100.

Panel A: Correlation Matrix

Variable	Cash	Options	Futures	E-Mini
Options	0.454			
Futures	0.492	0.352		
E-Mini	0.708	0.448	0.651	
ETF	0.574	0.362	0.474	0.656

Panel B: Coefficients of VIX

Variable	Coefficient	t-statistic
Cash	0.128	3.66
Options	0.618	7.07
Futures	0.362	5.56
E-Mini	0.426	7.68
ETF	0.647	9.00

Table 4 contd. on next page

Table 4, contd.

Panel C: Granger Causality Tests
[Null hypothesis: Row variable does not Granger-cause column variable]

	Cash	Options	Futures	E-Mini	ETF
Cash	-	7.27 (0.06)	48.55 (0.00)	48.07 (0.00)	60.02 (0.00)
Options	2.45 (0.48)	-	3.31 (0.35)	2.71 (0.44)	10.78 (0.01)
Futures	10.64 (0.01)	4.35 (0.23)	-	15.11 (0.00)	3.83 (0.28)
E-Mini	20.21 (0.00)	17.37 (0.00)	4.87 (0.18)	-	36.80 (0.00)
ETF	15.42 (0.00)	13.93 (0.00)	6.70 (0.08)	3.70 (0.30)	-
All	61.88 (0.00)	76.66 (0.00)	111.13 (0.00)	70.65 (0.00)	98.39 (0.00

Panel D: Variance Decomposition (%) from the VAR
[Columns represent the percentage of forecast error variance explained for the variable in the relevant row]

Variable	Options	Futures	E-Mini	ETF	Cash
Ordering: Options, Futures, E-Mini, ETF, Cash					
Options	95.21	1.38	1.75	0.56	1.10
Futures	7.78	88.25	1.28	0.31	2.38
E-Mini	19.38	30.75	46.02	0.20	3.65
ETF	15.49	12.72	18.31	48.64	4.84
Cash	19.49	13.55	19.68	1.54	45.74
Ordering: Cash, Options, Futures, E-Mini, ETF					
Options	73.88	1.20	2.48	0.85	21.61
Futures	1.60	84.31	0.05	0.18	13.86
E-Mini	0.13	16.68	39.55	0.13	40.22
ETF	4.39	5.31	13.20	49.41	27.69
Cash	0.29	0.16	0.91	1.44	97.20

Table 5: Volume and the Macroeconomy

Panel A presents summary statistics and contemporaneous correlations between daily log volumes and absolute values of the daily changes in macroeconomic variables and the absolute percentage return on the S&P 500 index. Mean and Sigma are the daily sample average and standard deviation respectively. Panel B presents regressions where the dependent variable is the absolute daily change in three macroeconomic variables and the absolute return on the S&P 500 index. The three macroeconomic variables are the following: (i) the short-term interest rate (ii) the term spread, and (iii) the credit spread. The term spread is the yield differential between constant maturity ten-year Treasury bonds and Treasury bills that mature in three months. The credit spread is the yield differential between bonds rated Baa and Aaa by Moody's. The right-hand volume variables represent the sum of three lags of logged daily volume for the S&P 500 Index (Cash), and for S&P 500 options (calls plus puts), legacy index futures, E-Mini futures and the "Spider" ETF. The variable LagDepVar is the average three-day lag of the dependent variable. The time-period is September 1997 through December 2009. Volume is in number of contracts, and all volume coefficients in Panel B are multiplied by 1000. The Newey and West (1987) method to correct for heteroskedasticity and residual autocorrelation is used with eight lags to compute the t-statistics in Panel B.

Panel A: Summary Statistics and Contemporaneous Correlations

	Mean	Sigma	Cash	Options	Futures	E-Mini	ETF	Short Rate	Term Spread	Credit Spread
	Summary Statistics		Correlations							
Cash	17.86	0.478								
Options	15.11	0.934	0.7816							
Futures	10.99	0.693	-0.2943							
E-Mini	12.74	1.650	0.7658							
ETF	17.36	1.386	0.7950							
Short Rate	0.0336	0.0561	0.1942	0.2405	0.0747	0.0439	0.1143			
Term Spread	0.0538	0.0583	0.2253	0.2796	0.0266	0.1416	0.2022	0.6577		
Credit Spread	0.0118	0.0192	0.1866	0.2345	-0.0300	0.1603	0.2084	0.0928	0.1667	
S&P 500	0.9370	0.9851	0.1938	0.2937	0.1694	0.0836	0.1822	0.1752	0.2482	0.2197

Table 5 contd. on next page

Table 5, contd.

Panel B: Predictive Regressions

Variable	Short-term interest rate		Term Spread		Credit Spread		Stock Market	
	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.	Coeff.	*t*-stat.
Cash	3.856	2.79	2.335	1.54	-0.488	-1.20	-0.218	-0.87
Options	1.283	1.62	2.177	2.32	1.000	2.76	0.520	3.07
Futures	2.005	2.53	1.625	2.20	0.195	1.08	0.289	2.76
E-Mini	-1.379	-2.77	-1.218	-1.89	-0.198	-0.94	-0.316	-2.52
ETF	0.872	1.10	1.461	1.53	0.437	1.28	0.361	2.03
LagDepVar	0.213	11.85	0.152	7.88	0.139	8.67	0.141	10.86
Intercept	-0.311	-3.62	-0.278	-3.26	-0.034	-1.66	-0.023	-1.95
Adjusted R^2	0.328		0.177		0.142		0.156	

Table 6: Predictive Absolute Return Regression Around Macroeconomic Announcements

In this regression, the dependent variable is the absolute S&P500 return on the date of the macroeconomic announcement. The right-hand volume variables represent the sum of three lags of logged daily volume for the S&P 500 Index (Cash), and for S&P 500 options (calls plus puts), legacy index futures, E-Mini futures and the "Spider" ETF. "Cashret" represents the compounded three lags of returns on the index. The time-period is September 1997 through December 2009. Volume is in number of contracts. Coefficients on volume variables are multiplied by 1000.

Dependent Variable: Absolute Announcement-Day Return

	Unemployment		CPI		GDP	
Variable	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Cash	-0.8528	-0.78	0.1410	0.12	0.2475	0.23
Options	1.7164	2.34	1.3314	2.01	0.8018	1.20
Futures	0.1924	0.30	0.5444	1.00	1.5880	2.18
E-Mini	0.2193	0.33	-0.0348	-0.14	-0.0530	-0.14
ETF	-1.0431	-1.09	-0.4467	-0.81	0.0128	0.02
|Cashret|	0.0461	0.77	0.2074	3.23	-0.0043	-0.08
Intercept	0.0178	0.31	-0.0550	-1.08	-0.0801	-1.52
Adjusted R^2	0.0486		0.1393		0.0433	

Table 7: Predictive Signed Return Regressions Around Macroeconomic Announcements Using Return-Signed Volume

In these regressions, the dependent variable is the signed S&P500 return on the date of the macroeconomic announcement. The right-hand volume variables represent the sum of three lags of the return-signed daily volumes for the S&P 500 Index (Cash), and for S&P 500 options, legacy index futures, E-Mini futures and the "Spider" ETF. The "return-signed volume" is the total volume of each explanatory variable multiplied by the sign of the concurrent daily return of the same variable (the sign is reversed for put volume). "Cashret" represents the compounded three lags of returns on the index. The time-period is September 1997 through December 2009. For scaling, each explanatory variable has been standardized (to a mean of zero and a standard deviation of 1.0) and the dependent variable has been divided by its standard deviation.

Dependent Variable: Signed Announcement-Day Return

	Unemployment		CPI		GDP	
Variable	Coeff.	t-stat.	Coeff.	t-stat.	Coeff.	t-stat.
Cash	0.2110	1.30	-0.1443	-0.86	-0.2963	-2.01
Options	-0.4427	-2.67	-0.3474	-2.14	0.0338	0.17
Futures	-0.1870	-1.62	-0.0089	-0.07	0.0092	0.08
E-Mini	0.3940	1.68	0.1718	0.81	0.0038	0.01
ETF	-0.0983	-0.44	0.1041	0.53	0.1331	0.40
Cashret	0.0469	0.40	0.2842	2.54	0.0873	0.71
Intercept	0.0908	1.12	0.0330	0.40	-0.0195	-0.23
Adjusted R^2	0.0437		0.0316		-0.0043	

Table 8: Correlations in VAR innovations and Granger Causality Tests Using Imputed Signed Volume

Panel A reports correlations in the innovations from a vector autoregression that includes ten endogenous variables (daily imputed signed volume of the S&P 500 Index, and of S&P 500 options, futures, and the ETF, the S&P 500 return, and first differences in the short rate, and the term and credit spreads) and one exogenous variable (VIX). Panel B reports the results of Granger causality tests (chi-squared statistics and *p*-values) which test whether imputed signed volume is useful in forecasting signed shifts in the macroeconomic variables (in a bivariate sense) after controlling for own-lags and lags of all of the other variables in the complete VAR. The time-period is September 1997 to December 2009.

Panel A: Correlations in VAR innovations

	S&P return	Short rate	Term Spread	Credit Spread
Options	0.619	0.155	0.021	-0.073
Futures	0.593	0.089	0.002	-0.016
E-Mini	0.585	0.139	0.040	-0.044
ETF	0.595	0.143	0.030	-0.052
Cash	0.672	0.122	0.041	-0.036

Panel B: Granger Causality Tests

[Null hypothesis: Row variable does not Granger-cause column variable]

	S&P return	Short rate	Term Spread	Credit Spread
Options	7.97 (0.05)	7.10 (0.07)	12.77 (0.01)	10.03 (0.02)
Futures	8.87 (0.03)	6.54 (0.09)	4.80 (0.19)	5.04 (0.17)
E-Mini	3.49 (0.32)	5.47 (0.14)	3.65 (0.30)	1.83 (0.61)
ETF	4.27 (0.23)	8.39 (0.04)	4.71 (0.19)	2.26 (0.52)
Cash	4.68 (0.20)	6.02 (0.11)	6.18 (0.10)	3.93 (0.27)

Figure 1. Volume for the S&P 500 and its Options, Spider, and Futures

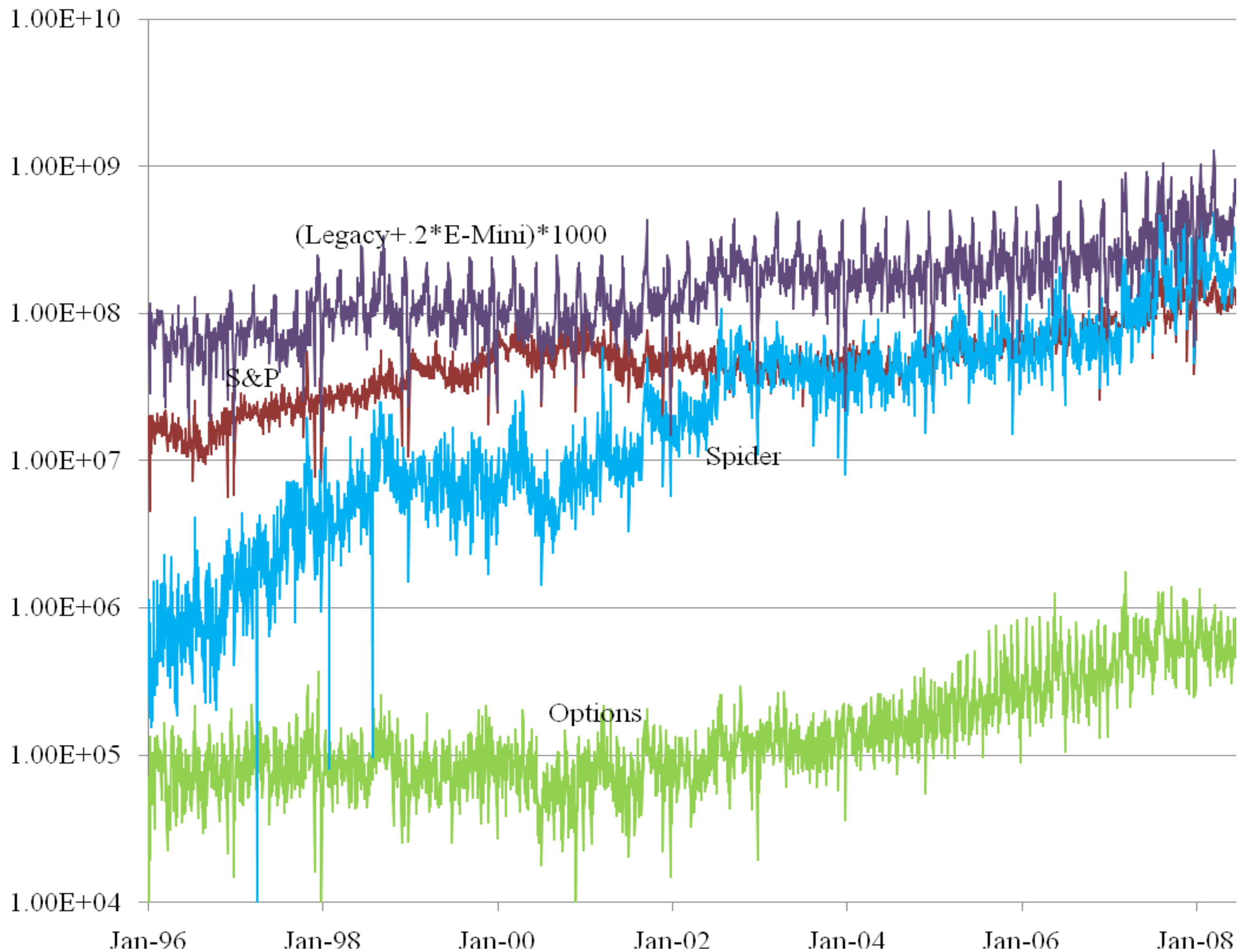

Figure 2. Contract Volumes of S&P 500 Legacy and E-Mini Futures

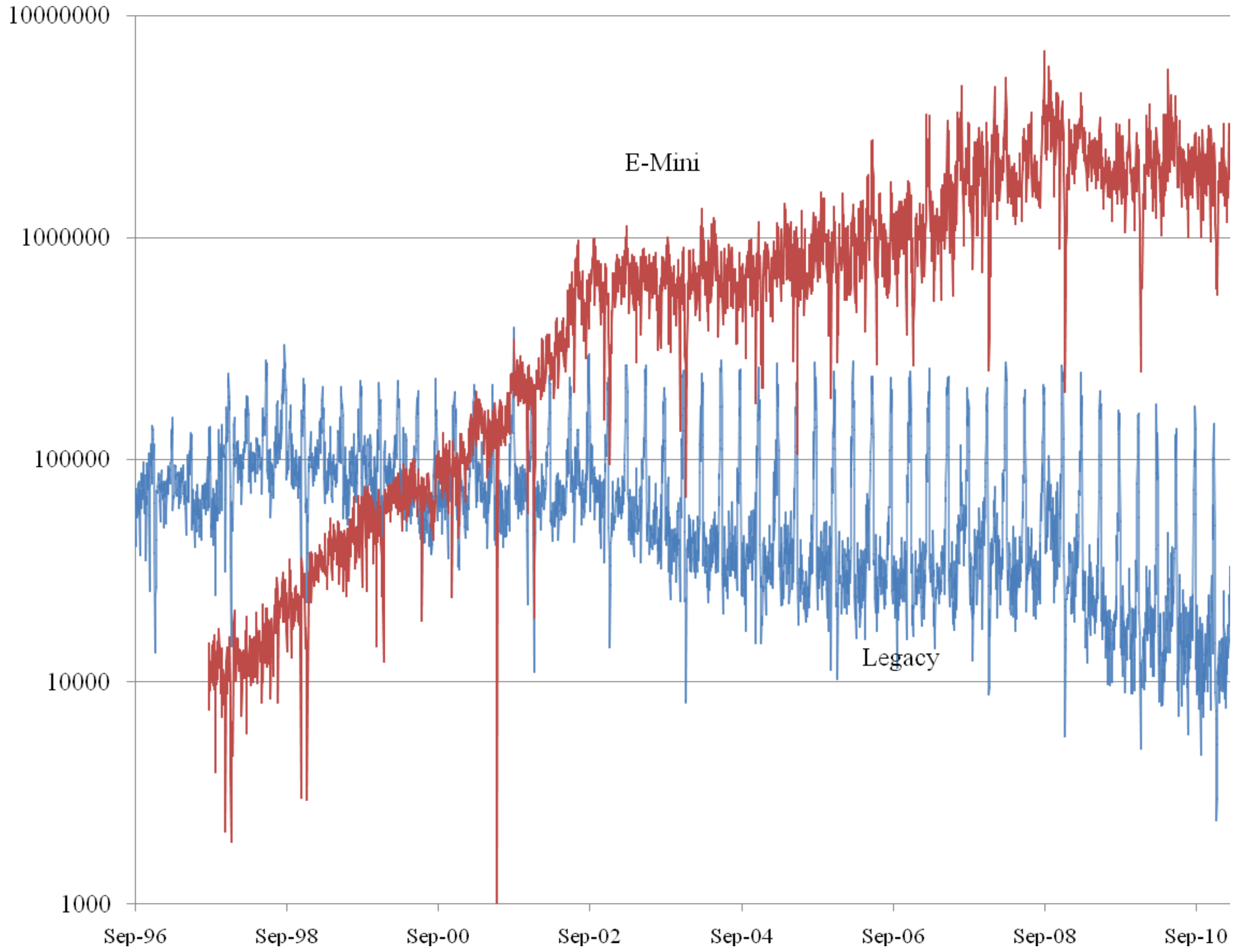

Figure 3: Generalized Impulse Response Functions

Here are impulse response functions from a VAR with daily volume for cash S&P 500 Index, and for S&P 500 options, futures, E-mini futures, and ETF. The time-period is September 1997 to December 2009. The data are the residual series from the regressions reported in Table 3.

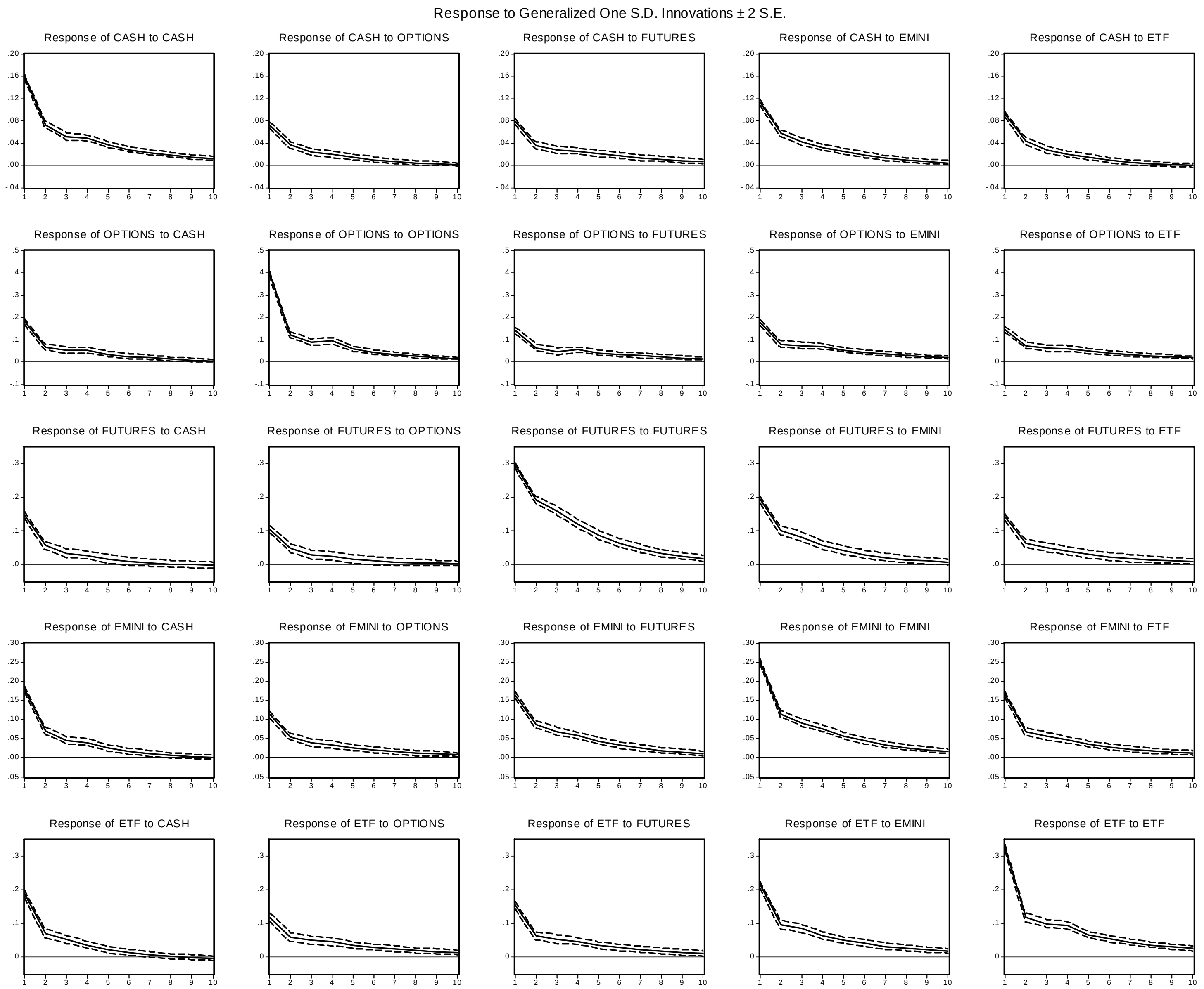

Figure 4: Impulse Response Functions Using Imputed Signed Volume

Here are impulse response functions from a VAR with ten exogenous variables (daily imputed signed volume for the cash S&P 500 Index, and for S&P 500 options, futures, E-mini futures, and ETF, and the S&P 500 and ETF returns, and first differences in the short rate, and the term and credit spreads), and VIX as an exogenous variable. The responses are calculated for the dependent variables: the S&P 500 return, and the first differences in the short rate, and the term and credit spreads, with respect to the imputed signed volume series. The time-period is September 1997 to December 2009.