Gamma Fragility

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Abstract

We document a link between large aggregate dealers' gamma imbalances and intra-day momentum/reversal of stock returns, arising from the potential feedback effects of delta-hedging in derivative markets on the underlying market. This channel relies on limited liquidity of the underlying market, but it is distinct from information frictions (adverse selection and private information) and funding liquidity frictions (margin requirement shocks). We test our joint hypothesis using a large panel of equity options that we use to compute a proxy of stock-level gamma imbalance. We find supporting evidence that intra-day momentum (reversal) is explained by the interaction of negative (positive) ex-ante gamma imbalance and and illiquidity. The effect is stronger for the least liquid underlying securities. Our results help to explain both intra-day volatility and autocorrelation of returns. Moreover, we find that gamma imbalance is related to the frequency and the magnitude of flash crash events.

Keywords: Frictions, Momentum, Option Markets, Risk Management, Gamma Imbalance, Flash Crashes, Liquidity

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A growing literature has documented the existence of temporary and permanent components in equity returns (Fama and French (1988), Daniel, Hirshleifer, and Subrahmanyam (1998)).[1] Some of these effects are found at daily frequencies (price spirals) while others manifest over longer horizons (momentum). In this paper, we focus on the first set of properties. Indeed, at intraday frequencies, several studies document that stock prices deviate from a random walk. Figure 1 provides a simple summary of the properties of the autocorrelation coefficient ρ of intraday returns sampled at 5-minutes frequency using non-overlapping observations based on a large sample of stocks in the TAQ dataset in the period 1996 to 2014. [2] On the y-axis the figure reports the probability that the absolute value $|\rho|$ is larger than $\bar{\rho}$ with $\bar{\rho} = 0.10, 0.20, \ldots, 0.90$. If stock prices were random walks, the autocorrelation coefficient ρ would be zero. The results strongly reject this hypothesis and show evidence of non-zero intraday autocorrelation. For instance, 22% of the time the autocorrelation coefficient is either larger than 0.2 or lower than -0.2. Moreover, if we run a regression of ρ on its lag we find that the slope coefficient is positive with a t-statistics equal to 32.17, suggesting a significant persistence of ρ at the stock level.

These properties are not only statistically strong but also interesting from an economic point of view as they deviate from what one would expect in a simple frictionless market. Therefore, a natural question that emerges is whether these patterns are the outcome of some deeper structural properties of financial markets.

The literature has proposed a few explanations to explain some of these regularities. A first explanation emphasizes the role played by economic frictions, such as margin requirements and capital constraints, in the formation of price spirals (Brunnermeir and Pedersen (2009)) and excess volatility. However, these explanations find it difficult to explain the existence,

[1] Examples include under- and over-reaction to news, momentum, mean reversion, excess volatility, and price spirals.

[2] This provides us with 4,777 trading days and 2,417,788 observations of ρ_i across all stocks i.

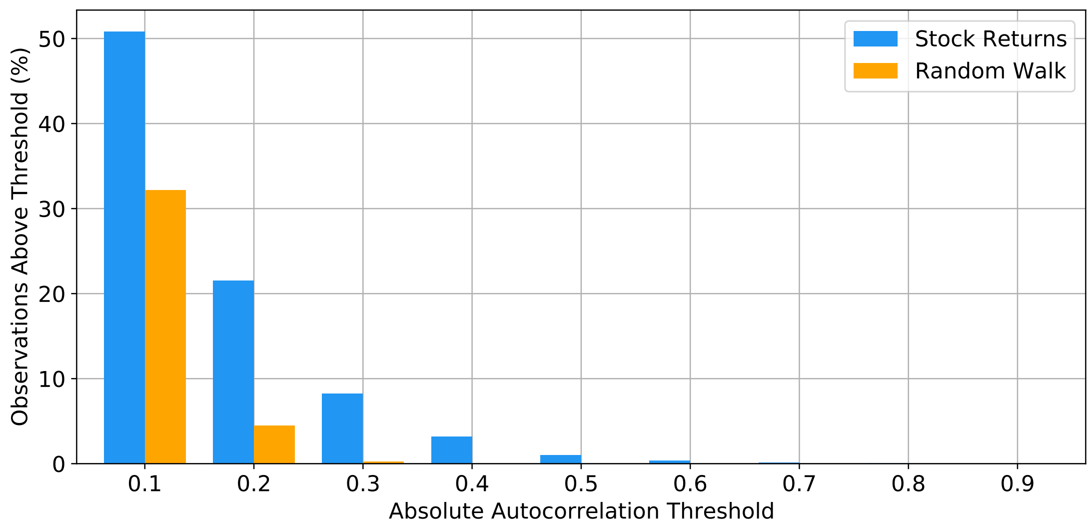

Figure 1. Magnitude of Intra-day Autocorrelation
The figure describes the magnitude of autocorrelation of intra-day stock returns. We define $\rho = \rho(j, d)$ as the auto-correlation coefficients of 5-minutes returns of stock j during day d, thus based on 96 non-overlapping observations. The figure displays the probability that $|\rho| > \bar{\rho}$ for $\bar{\rho} \in [0.1, 0.2, \ldots, 0.9]$, based on the empirical distribution of ρ sampled for a set of 2700 individual U.S. equity stocks over the period from 1996 to 2017 (2,417,788 observations).

at the same time, of both positive and negative autocorrelations. A second explanation builds on how information gets incorporated into asset prices. Easley, O'Hara, and Srinivas (1998) formally study a model that allows for endogenous participation of informed traders in the options market. They show the existence of a pooling equilibrium in which informed investors use both option and stock markets if the leverage implicit in options is large and the liquidity in the stock market is low. As a result, equity returns may display predictability. Pan and Poteshman (2006) find supporting evidence for the existence of an information-based channel linking the trading activity of privately informed traders in the options market and predictability in stock returns. Indeed, several studies have argued that informed investors might choose to trade derivatives because of the higher leverage offered by such instruments, e.g. Black (1975). A third growing literature emphasizes the importance played by behavioral biases.[3] This paper focuses on a different type of friction that is linked to the role played by the derivative market during periods of market illiquidity. It differs from information-based explanations and it may occur even in the absence of margin and capital constraints.

In the last 20 years, the use of derivatives for hedging has seen a massive increase due both to growing emphasis on asset-liability management and to explicit regulatory constraints. Solvency II, Dodd-Frank, and the EMIR Risk Mitigation Regulation increased the cost of capital in favor of risk mitigation techniques including hedging and reduction of counterparty risk. In particular, insurance companies have increased their use of derivatives to manage the embedded optionalities which are normally provided as part of their contracts and reduced the use of reinsurance. As a consequence, in 2017 the notional value of insurance industry derivatives reached $2.3 trillion, with roughly 95% held by life/annuity insurers and with options constituting 43% of this exposure.[4]

The aggregate net positions of options is by definition equal to zero. However, there is significant heterogeneity in the positions of different types of options (over maturity and strikes) across different types of institutions. This reflects institutional differences in preferences, technologies and possibly different strategic objectives across institutions and retail investors in the supply chain of options. In equilibrium, the risk is transferred over the option supply chain to market makers who are left, depending on their risk aversion, with the ultimate task to manage their risk exposure using dynamic hedging techniques. See Figure 2.[5]

[3]Initial underreaction to new fundamental information has been linked to the disposition effect (Frazzini (2006), Barberis and Xiong (2009), Shefrin and Statman (1985), Ben David and Hirshleifer (2012)). Daniel, Hirshleifer, and Subrahmanyam (1998) and Luo, Subrahmanyam, and Titman (2018) argue that the overestimation of one's own precision of private information signals (own ability) can help explain post-corporate post-earnings announcement stock price 'drift', negative long-lag autocorrelations (long-run 'overreaction'), and excess volatility of asset prices. Moreover, if in addition agents are affected also by a self-attribution bias, one may justify momentum (positive short-lag autocorrelations).

[4]See, Best's Special Report (2018), "Growing Use of Derivatives for Liability Risk Management".

[5]No market maker would simply sell puts (or call) options to hold the naked position on the underlying asset overnight. Such directional bets would simply be too large and not justifiable.

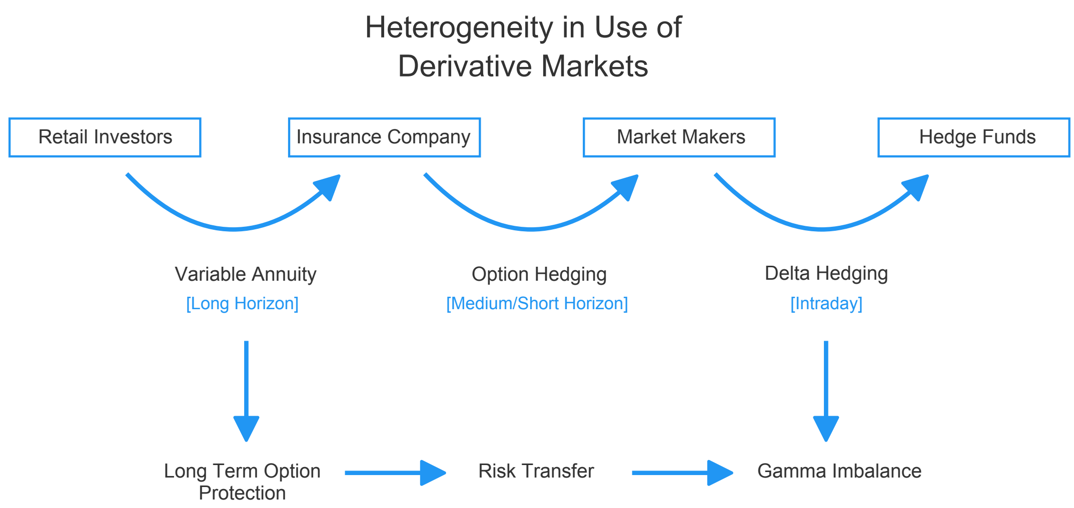

Figure 2. Risk Transfer in the Supply Chain of Options Markets

In absence of any risk management, a dealer profit profile is potentially very volatile and non-linear. To limit their market exposure, most dealers delta-hedge by selling shares of the underlying asset. The optimal amount of shares to buy (sell), however, changes depending on the intraday fluctuations of the underlying price. When the aggregate market gamma imbalance of dealers is large, the overall intraday activity of financial intermediaries may be substantial and may add additional pressure to an initial move of the underlying asset, giving rise to intraday *momentum (mean-reversion)*. The potential role of this channel to help to explain these observed effects depends on the extent of heterogeneity in both the supply chain of options and on the incentives by market makers to hedge intra-daily. Differently than individual investors, most market makers have an institutional mandate to hedge their derivative positions by the end of the trading day. However, the specific dynamics during the day typically vary among dealers.

The sign of the intraday serial correlation is opposite depending on the aggregate composition of the book. This provides an interesting set of joint testable implications. Let us define the aggregate dollar value of all market makers outstanding gamma with their clients as the *gamma imbalance,* which accounts for all options positions of different strike prices and maturity. When the aggregate gamma imbalance is large and negative, one should observe larger market volatility and short-term momentum (positive serial autocorrelation). On the other hand, when the gamma imbalance is positive, one should observe lower than average volatility and short-term mean reversion (negative serial autocorrelation). Notice that this specific effect is independent of the presence of *information* frictions, such as order flow toxicity, and of the additional role played by economic frictions such as margin constraints. It does, however, require that the market is not infinitely liquid to absorb intraday market makers demand shocks. This suggests an additional testable implication: the effect should be stronger (in the cross-section) for less liquid stocks and (in the time-series) during less liquid times since in a perfectly liquid and frictionless market options are redundant assets and no feedback effect should exist between options and their underlying. Our question is related to the work of (Ni, Pearson, Poteshman, and White 2018) who investigate the empirical link between delta-hedging and the volatility of the underlying stock by using daily net open interest and signed volume data of different investors. Our work studies the effect of this channel on the emergence of intraday momentum/reversion and the probability of flash crashes occurring at both the individual stock and index level. Moreover, since our sample covers a more recent and more extended time period, we document the robustness of the interaction of market frictions and gamma imbalance on stock volatility in the post May 6^{th} 2010 Flash Crash, after the CFTC introduced a series of regulatory restrictions.

To investigate the extent to which gamma imbalance can help to explain the observed intraday patterns in equity markets, we use option trading data from three Nasdaq exchanges (ISE, GEMX, and PHLX), including opening and closing volume for broker/dealers, firm, customer, and professional trades. We merge these with the IvyDB dataset from OptionMetrics to construct a comprehensive dataset of equity options that include both index and a large cross-section of individual stock options. Information on both open interest and option specific greeks are used to obtain a panel on day- and security-specific gamma imbalance of broker/dealers in the option market. The dataset covers the period between 2010-2020. Intra-day returns and the trading volume for each of the underlying assets are from TAQ. The cross-sectional dimension of the dataset is important since at each given point of time, a large number of assets have negative and positive gamma imbalance. This helps to identify the effect and increases the power of our tests.

We focus on three main questions. First, what is the extent to which gamma imbalance explains asset volatility? Limited market liquidity and the existence of an institutional friction suggests that volatility is larger when gamma imbalance is more negative. We run a panel regression of the absolute value of the return of underlying asset j on day t on our proxy for the gamma imbalance of options dealers measured at time $t-1$. As predicted, the data shows a negative relationship between daily return volatility and gamma imbalance. The results are strongly statistically significant and robust to a series of controls, such as alternative definitions of intraday volatility and after conditioning for time and other common effects. Moreover, using the cross-sectional dimension of the dataset, we find that the increase in volatility during negative gamma days is significantly stronger for the least liquid assets. This is consistent with the hypothesis of a dealer order flow friction that becomes more binding in illiquid markets.

Second, what is the extent to which gamma imbalance explains intra-day momentum and reversal? We run a panel regression of the autocorrelation coefficients of h-minute returns of stock j onto date and security-specific gamma imbalance. We find that the slope coefficients are negative and statistically significant, supporting the null hypothesis. We also find that the magnitude and significance of the coefficients is increasing with the frequency and peaks at a horizon of $h = 60$ minutes, consistent with an economy in which dealers adjust their delta-hedged portfolios intraday at a similar frequency.

Finally, we investigate the link between gamma imbalance and flash crashes, that is, large price drops materializing over a short time period. Using the "drift burst" detection methodology proposed by Christensen, Oomen, and Renò (2018), we identify a panel of flash crash events and study their relationship to gamma imbalance. We find that conditional on negative ex-ante gamma imbalance flash crashes are more likely to occur and larger in magnitude. This effect is economically significant across our entire sample.

Related Literature. This paper is related to several streams of the asset pricing literature. A first stream studies the relation between economic frictions, liquidity, and market fragility – see, among others, Holmstrom and Tirole (1997) and Brunnermeir and Pedersen (2009). The last investigate the link between an asset's market liquidity (i.e., the ease with which it is traded) and traders' funding liquidity (i.e., the ease with which they can obtain funding). They show that, under certain conditions, margins are destabilizing and market liquidity and funding liquidity are mutually reinforcing, leading to liquidity spirals. They argue that speculators' capital can become a driver of market liquidity and risk premiums. Their work is part of a growing literature.[6]

Our work is also related to an important literature that studies the impact of asymmetric information and adverse selection in the context of informed trading on asset prices. Information-based models (e.g., Glosten and Milgrom (1985), Easley, O'Hara, and Srinivas (1998)) suggest that while stock prices will fully adjust when all public information is revealed, they may gradually adjust to the private component of information. As a result, stock returns may display predictability and serial correlation. Pan and Poteshman (2006) test this hypothesis using information from options markets and show that stocks with low put-call ratios outperform stocks with high put-call ratios by more than 40 basis points on the next day and more than 1% over the next week. They interpret the economic source of this predictability as private information possessed by options traders rather than market inefficiency. Our result focus instead on the emergence of intra-day predictable variation in

[6]See among others, Adrian, Moench, and Shin (2014), Gromb and Vayanos (2002), Garleanu and Pedersen (2001), Adrian, Etula, and Muir (2014), Adrian and Shin (2010), Adrian and Boyarchenko (2015), Adrian, Colla, and Shin (2012).

stock prices and market fragility even in absence of private information.

Our paper provides further evidence suggesting that trading on derivatives may affect the price of the underlying securities. Ben-David, Franzoni, and Moussawi (2018) shows that the arbitrage activity of market makers in the ETF market generates excess volatility on the underlying stocks. Shum, Hejazi, Haryanto, and Rodier (2015) find that leveraged ETFs drive up volatility near the market's close because of hedging activities of ETF providers.

Our paper relates also to a third stream of the literature that investigates the effect of institutions on asset prices. In this area, important works include Vayanos and Woolley (2013) and Gorton, Hayashi, and Rouwenhorst (2013). The first suggests a theory of momentum and reversal based on flows between investment funds. They argue that flows are triggered by changes in fund managers' efficiency, which investors either observe directly or infer from past performance. Momentum arises if flows exhibit inertia, and because rational prices under-react to expected future flows. Reversal arises because flows push prices away from fundamental values. Hendershott and Seasholes (2007) study explicitly the link between non-informational order imbalances (buy minus sell volume) to predict daily stock returns at the market level.[7]

I. An Example: General Motors

To illustrate the potential effect of gamma imbalance on intraday stock price dynamics, consider the time series properties of General Motors stock price on October 13^{th} 2014 and on January 9^{th} 2009. Figure 3 summarizes the two time series. The first panel displays the evolution of the price on October 13^{th} 2014, when the gamma imbalance of option dealers on GM at the beginning of the trading day was deeply negative, amounting to more

[7] Additional evidence on the role of institutions in the correlations of asset returns is also discussed in Anton and Polk (2014), Chang, Hong, and Liskovich (2013), Greenwood and Thesmar (2011), Lou and Polk (2013), and Jotikasthira, Lundblad, and Ramadorai (2012).

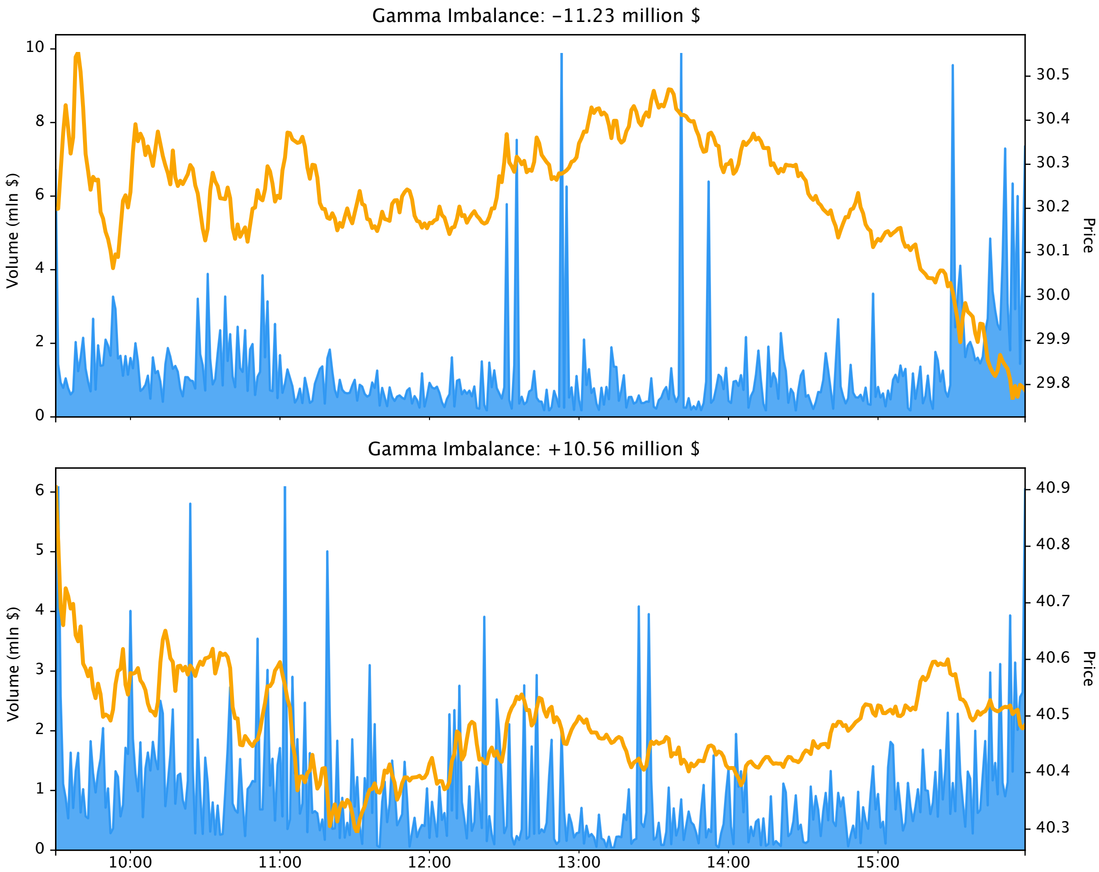

Figure 3. General Motors Stock Price

than 11 million dollars. This is a significant amount, equivalent to more than 21% of the average hourly volume for the underlying stock. If the imbalance is due to short OTM put options positions, intermediaries can limit their market exposure by delta-hedging with short positions in the stock. At around 13:30 the price starts dropping sharply, driving a large amount of put options closer to being ATM. Thus, to maintain a constant delta exposure, intermediaries should increase their short positions by selling more stocks. As the stock price continues to fall throughout the rest of the trading day, delta-hedging would induce dealers to increase even further their short positions. The effect is particularly strong during the last 30 minutes of the trading day when we observe a significant rise in trading volume. On this day, we find that the autocorrelation of hourly returns is +43%. Our conjecture is that the automatic risk-management order flow has contributed to the intraday momentum. The bottom panel shows another, albeit opposite, example. At the beginning of January 9^{th} 2009, the aggregate gamma imbalance was significantly positive, due to long OTM call options positions. If the intermediary wanted to hedge market exposure, delta hedging would require the dealer to short the underlying asset. In this case a price drop reduces the call option's delta, thus inducing intermediaries to buy back some equity. If the flow is significant relative to the available liquidity, it could dampen the initial negative price shock. Consistently, the plot shows evidence of strong intra-day mean reversion with an autocorrelation coefficient equal to −63%. In these two examples, the sign of the autocorrelation coefficient is negatively related to the sign of the ex-ante aggregate gamma imbalance. Moreover, while in the first example the intraday (annualized) volatility is 24%, which is above the unconditional average, in the second case the volatility is at 18%, below the average. Are these two examples simply a coincidence or are they revealing the existence of an important friction?

II. Data and Summary Statistics

This section discusses the data sources, the definition of the main variables we use and documents the main summary statistics.

A. Data Sources

Our empirical analysis is based on a number of data sources. To construct the inventory of option contracts held by broker/dealers, we use option trading data from three Nasdaq exchanges (ISE, GEMX, and PHLX). These datasets provide opening and closing volume for broker/dealers, proprietary trading desks, and private customers, covering the period between January 2010 and May 2020. In this time window, these three exchanges account for a fraction between 10% and 20% of the worldwide dollar volume of option contracts written on US equity securities[8]. We obtain data on daily options prices, open interest, and greeks from the IvyDB dataset provided by OptionMetrics. After merging these 4 data sources, the resulting sample covers put and call options for 3491 U.S. individual stocks. We also include options on 4 broad market indices to the sample, which are available from OptionMetrics.We merge the dataset obtained with the CRSP and TAQ databases by ticker to obtain information on daily and intra-daily returns and trading volume for each underlying assets. We collect data on market fundamentals from the News Analytics dataset by RavenPack, which provides sentiment scores that is useful to identify asset-days with significant news. The final sample includes four market indices (S&P 500, Dow Jones, Nasdaq 100 and Russell 2000) and 2700 individual U.S. equity stocks. Our panel is, by construction, unbalanced because some of the single-name options enter the sample only when they start being traded.

Figure 7 shows the distribution of intra-day autocorrelation coefficients for equity returns sampled at 5-minutes intervals. We cannot reject the null hypothesis that the unconditional average of the autocorrelation coefficient is zero. However, we find strong evidence of both conditional intra-day momentum (positive autocorrelation) and reversal (negative autocorrelation). Indeed, about 13% (8%) of the days had an intra-day autocorrelation greater than $+0.20$ (lower than -0.20).

Insert Figure 7 here

B. Gamma Imbalance

Let the value of the underlying asset at time t be S_t. The delta Δ_t of an option $C_t(S_t; K, T)$ is defined as the first derivative of the option price with respect to the underlying price $\Delta_t = \frac{\partial C}{\partial S_t}$. At time t, delta-hedging of an option portfolio requires buying or selling an amount of the underlying asset equal to $-\Delta_t$. Since changes in S_t changes the value of Δ_t,

[8]We are currently in the process of obtaining additional data from the CBOE C1 exchange. In that way, we would extend our coverage to almost 50% of the total dollar volume

delta hedging strategies require a dynamic adjustment of the position on the underlying asset. The greek Γ_t measure the rate of change of Δ_t given a change in the underlying asset, i.e. $\Gamma_t = \frac{\partial \Delta_t}{\partial S_t}$, and is proportional to the convexity of the value of the derivative security with respect to S_t. Both call and put options are convex in S_t. Thus, a long portfolio of options implies a positive Γ_t, which implies that the size of the delta-hedging position is positively related to the underlying price. On the other hand, a short portfolio of options implies a negative Γ_t, i.e. the size of the delta-hedging position is negatively related to the underlying price.

Financial institutions heavily rely on option markets to transfer some of the risk embedded in the contracts offered to their clients. The traded options market has become a solution of choice, due to their liquidity and limited counter-party risk. A large literature documents that in certain periods the book of financial intermediaries can be imbalanced. This would occur, for instance, when the aggregate demand of their customers contributes to a build-up of an excess demand for either puts or calls in a particular index or individual stock. We are interested in a measure of this imbalance (the gamma imbalance) and compute it at the day and asset-specific level.

Our data allows us to directly observe the trading volume of option contracts broken down by category of market participants. In particular, we observe trades by broker/dealers, market makers, investment banks' proprietary trading desks (firms) and private customers. For each option, we compute the daily inventory held by each category category following the procedure outlined in (Ni, Pearson, Poteshman, and White 2018). We assume that only broker-dealers and market makers are involved in delta-hedging. Thus, the total delta-hedgers' inventory fort a given option j on day t is computed as:

$$\text{Hedgers Inventory}_j = \text{BrokerDealers Inventory}_j - \text{Customers Inventory}_j \tag{1}$$

Since each option has a gamma which depends on its moneyness and time to expiration, we compute the gamma exposure of each specific call and put option on each trading day t. The aggregate hedgers' Gamma exposures on stock i on day t is computed as the gamma-weighted sum of inventories across the options written on that stock:

$$\text{Hedgers Gamma}_i = \sum_{j \text{ written on } i} \Gamma_j \times \text{Hedgers Inventory}_i ,$$

where Γ_j is provided by OptionMetrics. Our main quantity of interest is the broker/dealers' Gamma Imbalance for stock i, that is, the fraction of delta-hedgers' dollar volume induced by a 1% price movement as a fraction of the average daily volume, in percentage terms. Formally, it is defined at the daily frequency by

$$\Gamma_i^{IB}(t) = \text{Hedgers Gamma}_i \times \frac{S_i(t)}{ADSV_i(t)} \tag{2}$$

where $S_i(t)$ is the market price of stock i at the end of day t, and $ADSV_i(t)$ is the average daily share volume for the stock computed on a 21-day rolling window ending one trading day before day t.

Table I reports summary statistics on Γ^{IB} and the open interest for the option contracts in our sample. We also report statistics on the implied volatility, computed as the average across all outstanding contracts for each day-asset pair. Our identification strategy is based on both the time-series and the cross-sectional variation of Γ^{IB}. In Figure 4, the darker line highlights the cross-sectional average on each date t; the light (dark) shaded area represents the 10th and 90th (25th and 75th) percentiles interval of the daily distribution of Γ_1^{IB}.

Two main properties emerge. First, on almost every day in the sample Γ_1^{IB} ranges from significant negative to positive values across different individual stocks. Moreover, the cross-sectional average displays rich time-variation. These two properties are important since our identification strategy uses both time-series and cross-sectional variation.

Insert Figure 4 and Table I here

Two channels drive the time-variation in Γ^{IB}. The first one is due to a quantity effect: the portfolio decision of institutional and retail investors to buy/sell options and the willingness of option dealers to accept the trade. The second one is due to a price effect: the endogenous impact on Γ^{IB} induced by a variation in the price of the underlying asset. This second effect depends on the entire distribution of the moneyness and maturities of the call and put options held in dealers' book; intraday shocks to the underlying price have immediate implications on the aggregate Γ^{IB}. Figure 5 shows the relative importance of the two channels.

On November 15th, 2018, the S&P500 index was 2,730.27 and the aggregate Γ^{IB} outstanding was negative. As the blue curve shows, an increase in the S&P500 would also increase Γ^{IB} and, in absence of other portfolio changes, the aggregate Γ^{IB} would change sign and become positive if the S&P500 were to move above 2762.5 (a 2.3 percentage move). The shape of the curve depends on the specific distribution across moneyness and maturity of the dealers' options book. Keeping constant the S&P500 level, one can compare the relative importance of these two channels, on this particular day, by comparing the vertical distance between the two curves (quantity effect). Our data allows us to track this information at the daily frequency.

Insert Figure 5 here

III. Empirical Results

In this section, we present the main empirical results of the paper. We articulate our analysis around three main null hypotheses.

A. Volatility and Gamma Imbalance

The first empirical null hypothesis relates to the assumption that dealers' order flow in the underlying assets has a non-trivial intra-day price impact.

$H0_1$: *Does Gamma Imbalance help to explain intraday market volatility?*

We investigate the existence of a negative link between daily volatility and dealers' gamma imbalance. When dealers' gamma is positive (negative), their delta increases (drops) when the underlying asset increases. Thus, their delta-hedging strategy requires selling (buying) more of the underlying asset following an increase in the underlying price. Therefore, dealers order-flow acts as a contrarian (reinforcing) force, thus limiting (strengthening) the magnitude of initial price movements.

It is important to notice that there are many reasons why one may expect the null hypothesis to be rejected. First, dealers may be less risk-averse than commonly perceived and less interested to aggressively hedge their delta imbalances. Second, the underlying asset market could be sufficiently liquid and frictionless so that dealers' delta hedging strategies have no price or volatility impact. Third, dealers could be extremely rational and technologically sophisticated to be able to implement hedging strategies with no aggregate price impact. Fourth, while this channel might be realistic, it might not be sufficiently strong to dominate other equally important channels. Finally, the construction of a proxy of gamma imbalance is notoriously difficult due to regulatory restrictions that, in some cases, limit the amount of information necessary to identify all trading counter-parties. The noisier the proxy, the less powerful the test, and the more likely one may reject the null hypothesis $H0_1$ even if there were a relationship, thus biasing the test against finding a result.

To test this hypothesis we run a panel regression of absolute returns on stock j conditional on the aggregate gamma imbalance of option dealers $\Gamma^{IB}_{j,t-1}$ for security j at time $t-1$:

$$|R_{j,t}| = \alpha + \beta_0 \Gamma^{IB}_{j,t-1} + \beta_1 IVOL_{j,t-1} + FE_{j,t} + e_{j,t}, \tag{3}$$

where the term $FE_{j,t}$ refers to different time and asset fixed-effects. Standard errors are clustered by asset and month to allow for arbitrary correlation structures both in the time series and cross-section. We control for the previous day implied volatility $IVOL_{j,t-1}$ computed as the average across all outstanding options written on stock j.

The results are summarized in Table II and show that the coefficient on $\Gamma^{IB}_{j,t-1}$ is negative and highly significant with a t-statistics ranging between -5.07, after controlling for lagged implied volatility, and -12.08, after controlling also for asset and month fixed effects. Indeed, consistent with our null hypothesis, the data shows a negative relationship between daily volatility of returns and gamma imbalance. In column two, three, and four we control for asset, time, and both time and asset fixed effects, respectively. The statistical significance of the results are even stronger. These results are also significant from an economic standpoint. The estimates imply that one standard deviation in the gamma imbalance is associated to a decrease between 5 and 25 basis points in the absolute value of the daily return for the underlying stock. This constitutes an economically significant impact, given that absolute daily returns average at 180 basis points in our sample.

Insert Table II

Figure 6 (top panel) shows the distribution of t-statistics of the estimator of β_0 when we run time-series regressions for individual stocks in our sample. T-statistics are computed using the heteroskedasticity and autocorrelation consistent (HAC) standard errors from Newey and West (1986). We find that the distribution is strongly shifted to the left (of zero): for 70% of the stocks in our sample the t-statistic is negative. This highlights a strong negative link between aggregate Gamma Imbalance and returns volatility also for individual stocks.

Insert Figure 6

Next, we investigate whether there are differences in the impact of the gamma imbalance for options written on indices versus individual stocks. We expect the effect to be statistically and economically stronger for index options for both statistical and economic reasons. Indeed, the open interest on index options is significantly larger than that of single-name options and the aggregate gamma imbalance measure is likely to be a more precise proxy of the real gamma imbalance of dealers. However, as our data from Nasdaq exchanges does not contain information about index options, we are not able to measure directly the gamma profile of broker/dealers. We thus fall back to a different proxy for dealers' gamma imbalance that can be derived from OptionMetrics, relying on the assumption that most investors have short positions on calls and long positions on puts (collar strategy). Although imperfect, this assumption is backed by empirical evidence (Garleanu, Pedersen, and Poteshman (2008)). Since broker/dealers are on the other side of the trade, they are mostly long call options and short put options. Their aggregate imbalance is thus proportional to the difference between the aggregate gamma of the call minus the aggregate gamma of the put options, $\Gamma^{\$}_{Call}(t) - \Gamma^{\$}_{Put}(t)$. Accordingly, we define our first proxy $\Gamma^{\$}_{1}(t)$ as a fraction of the average daily volume for the underlying security:

$$\Gamma_1^{IB}(t) = \left[\Gamma^{\$}_{Call}(t) - \Gamma^{\$}_{Put}(t)\right] / \text{ADV}(t) \times 100. \tag{4}$$

We estimate the same regression model as in our baseline specification for four broad-market indices, namely S&P 500, Dow Jones, Nasdaq 100, and Russell 2000. Results are summarized in Table III and show that the coefficient on Γ_1^{IB} is negative and significant in all specifications. As expected, the slope coefficient is significantly larger for index options than for single-name options, ranging from -14.8 (after controlling for both asset and month fixed effects) to -5.5 (after controlling only for asset fixed effects). Moreover, the statistical significance is still high, and the t-statistics ranges between -4.4 (after controlling for lagged implied volatility and abnormal volume but no fixed effects) to −3.3 (after controlling for lagged implied volatility, abnormal volume, and both asset and month fixed effects). This is rather impressive since the sample is almost 1000 times smaller than the panel of individual stocks. The economic magnitude of the effect is even more striking, as one standard deviation increase in the gamma imbalance is associated to a decrease in absolute return of the underlying index of more than 20 basis points (about 20% of a standard deviation)

Insert Table III

Finally, since return volatility is known to be a highly persistent process, we re-run the panel regressions adding alternative variables to control for persistent components in the volatility process. Table IV summarizes the results. We find that in all these alternative specifications the coefficient on Γ^{IB} continues to be highly significant and roughly of the same (negative) magnitude.

B. Heterogeneity in Illiquidity

Empirical findings supporting $H0_1$ might suggest the existence of frictions in the derivative and underlying asset market. A potential channel for such a friction relies on option dealers generating price impact when rebalancing their delta-hedging positions. A testable implication of such a theory is that the effect of gamma imbalance on stock returns is more pronounced for less-liquid stocks, for which the price impact arising from option dealers trades should be larger in magnitude. Hence, to study in further detail the nature of these potential frictions, we investigate whether the effect of gamma imbalance is stronger in less liquid assets and in less liquid time periods:

$H0_2$: *Is the impact of Gamma Imbalance stronger during time periods and for stocks that are more illiquid?*

Since our Γ^{IB} proxy is expressed as a fraction of the average daily volume (ADV) of the underlying stock, and ADV is positively related to liquidity, our results described in the previous sections suggest that the magnitude of the gamma imbalance effect is inversely related to liquidity. To further test this hypothesis, we consider a *dollar* version $\Gamma^{IB}_{\$}$ of our Gamma Imbalance proxy, multiplying Γ^{IB} by the ADV of the relevant stock. We then compute the Amihud illiquidity ratio for each underlying asset at the daily frequency, using a rolling window of two years ending one month before the day of interest. We calculate the median value of each asset across the entire sample period and use the resulting asset-level illiquidity measure to split our universe into two equally-sized groups. Finally, we regress absolute daily returns on the interaction between $\Gamma^{IB}_{\$}$ and a dummy variable $I_{\mathcal{L}}$ indicating the most illiquid asset. Table V summarizes the results and specification (3) unveils a negative and significant (tstat -7.61) coefficient on the interaction term. The magnitude of the coefficient on the interaction term (-8.88) indicates that one standard deviation decrease in Γ^{IB} is associated to an increase in volatility of almost 9 basis points for illiquid stocks relative to more liquid ones, after accounting for illiquidity. This result implies that the increase in absolute returns during negative gamma days is significantly larger for the most illiquid assets. This finding supports our theory of a channel connecting gamma imbalance and stock return dynamics induced by the price impact of option dealers rebalancing their delta-hedging positions.

Insert Table V

More generally, this result can be interpreted as evidence of the importance of economic frictions for short-term asset price dynamics and relates to a growing literature that argues about the importance of these frictions. Brunnermeir and Pedersen (2009) argue that market liquidity and funding liquidity are mutually reinforcing, leading to excess volatility and liquidity spirals. Our results suggest that this may occur even in the absence of (in addition to) margin constraints through the interaction of market illiquidity and the risk-limiting behavior of risk-averse market makers.[9]

C. *Intraday Autocorrelation: The Role of Gamma Imbalance for Momentum and Mean-Reversion.*

An additional implication of the channel underlying hypothesis $H0_1$ directly relates to the existence of intraday market momentum or mean-reversion depending on the gamma imbalance. Indeed, dealers delta-hedging strategies require selling more of the underlying asset following an increase in the underlying price if their Gamma Imbalance is positive. The opposite effect occurs when the Gamma Imbalance is negative. Thus, dealers order-flow should act as a contrarian force when the Gamma Imbalance is positive giving rise to intraday mean-reversion, namely negative intraday autocorrelation. The opposite effect should emerge when the Gamma Imbalance is negative when one should expect intra-day momentum, i.e. positive intraday autocorrelation.

$H0_3$: *Equity serial autocorrelation is positive (negative) when dealers are short (long) gamma.*

To test this hypothesis, we use data from the TAQ database to compute the autocorrelation of returns for the equity stocks in our universe, at different frequencies. For each day-asset pair (t, j) we estimate the sample autocorrelation coefficient $\rho^h_{j,t}$ of h-minute non-overlapping returns with h = 5, 10, 20, 30, and 60. Then, we run the following panel regressions, for each frequency h

$$\rho^h_{j,t} = \alpha^h + \beta^h_0 \, \Gamma^{IB}_{j,t-1} + FE_{j,t} + \varepsilon_{j,t}, \tag{5}$$

We test the null hypothesis that $\beta^h_0 < 0$ at the intraday level. Results are reported in Table VI and show that the slope coefficients on $\Gamma^{IB}_{j,t-1}$ are indeed negative and significant for all the frequencies, supporting the null hypothesis $H0_3$. It is interesting to observe that the

[9] See also Adrian, Moench, and Shin (2014), Gromb and Vayanos (2002), Garleanu and Pedersen (2001), Adrian, Etula, and Muir (2014), Adrian and Shin (2010), Adrian and Boyarchenko (2015), Adrian, Colla, and Shin (2012).

magnitude of the coefficients are larger for $h = 5$ and $h = 60$. This is consistent with two frequency of portfolio rebalancing. Broker/dealers adjust their delta-hedged portfolios both at high-frequency (5 minutes) and at a lower frequency of about 60 minutes. The economic magnitude of these results is also significant. A unitary standard deviation increase in the gamma imbalance proxy is associated to a decrease in autocorrelation between 1.5% and 2%.

[Insert Table VI]

IV. Market Fragility and Flash Crashes

A growing literature studies market events that are characterized by a very rapid, deep, and transitory fall in security prices. These events are often referred as "flash crashes" and have been conjectured to originate from the interaction of automated high-frequency trading, spoofing and price manipulation, the fragility of derivative markets, and other automatic hedging strategies.

The literature on flash crashes gained particular vigour in the aftermath of the famous May 6, 2010 U.S. market crash that saw about a trillion dollar of market capitalization being wiped out in 36 minutes. The specific dynamics of how the crash occurred strike a familiar note. When U.S. stock markets opened, the Dow started trending down due to worries about the debt crisis in Greece. By 2:42 p.m. the Dow was down more than 300 points. After 2:42 p.m., the drop accelerated and the index fell an additional 600 points in 5 minutes accumulating a total loss of nearly 1,000 points by 2:47 p.m. Although the sharp drop was later reversed, the economic magnitude of the intraday volatility was remarkable given the absence of significant economic news.

The May 6 2010 Flash Crash was not an isolated event. Gao and Mizrach (2016) argue that flash crashes have occurred in almost every year in the period 1993-2011 that they study. The most notorious of these events have directly involved the index. However, individual stocks have also been exposed to similar events. Our hypothesis is that flash crashes are more likely to occur when markets are fragile. In our context, an important factor contributing to market fragility is the aggregate gamma imbalance.

To investigate whether gamma imbalance is potentially related to these events, first we construct a temporary proxy of intraday volatility that is particularly sensitive to intraday jumps. We use as dependent variable the daily spread, i.e. the difference between the intraday High and Low relative to the mid-point price (e.g., $Spread = \frac{H-L}{H+L}$). Then, for each day-asset pair (t, j) we run a regression of the $Spread(t)$ onto the lagged level of gamma imbalance $\Gamma^{IB}_{j,t-1}$ after controlling for fixed effects and lagged implied volatility:

$$Spread(j,t) = \alpha + \beta_0 \Gamma^{IB}_{j,t-1} + \beta_1 IVOL_{j,t-1} + FE_{j,t} + e_{j,t}. \tag{6}$$

We run four specifications. Specification (1) excludes fixed effects, while specifications (2) and (3) include controls for asset and month fixed effects. Specification (4) include both controls. The estimates are summarized in Table VII. Two main results emerge. First, the slope coefficient of a regression of *Spread* on lagged Γ^{IB} is negative and highly significant, suggesting that large negative values of the gamma imbalance correlates with increases in intraday price jumps. In all specification, the t-statistics are based on robust standard errors double-clustered at the asset and month level and indicate that lagged Γ^{IB} is statistically significant at the 1% confidence level.
Second, the economic significance of the effect on the intraday *Spread* is important. Indeed, in specification (4), which includes both asset and month fixed effects, the slope coefficient for $\Gamma^{IB}_{j,t-1}$ is -15.98. This estimate implies that a one standard deviation decrease in gamma imbalance is associated to an increase of roughly 16 basis points in the daily spread. This is consistent with the economic hypothesis that periods of large negative gamma imbalances are more fragile. Jumps and flash crashes are more frequent, and volatility is higher.

Insert Table VII

A. Flash Crash Identification and Tests

The previous results use the whole data and the dependent variable include both large and small events. In the following, we directly identify the subset of flash crashes in the data set to study the link with the gamma imbalance. Then, we test the hypothesis that the probability of a stock experiencing a flash crash increases when the stock is subject to negative gamma imbalance and decreases when its gamma imbalance is positive. Moreover, we investigate whether, conditional on a flash crash happening, the price drop is more pronounced for stocks exposed to negative gamma imbalances. These tests use both time-series and cross-sectional information.

We use the “drift burst” detection methodology proposed by Christensen, Oomen, and Renò (2018). This approach aims to identify “sudden and extreme movement in price which occurs in relatively short time and then reverts to the initial level” as opposed to simply a period of extreme volatility or a price jump. To illustrate their methodology, let us assume that p_t be the log-price price of the asset follows

$$dp_t = \mu_t dt + \sigma_t dW_t. \tag{7}$$

Moreover, assuming that the price process is observable over $[0, T]$ at some time points $0 = t_0 < t_1 < ... < t_n = T$, returns are defined as

$$r_{t_i} = p_{t_i} - p_{t_{i-1}}, \qquad i = 1, ..., n.$$

Christensen, Oomen, and Renò (2018) propose to compute of the current velocity of the market as defined by the test statistics

$$T_t^n = \sqrt{\frac{h_n}{K_2}} \frac{\hat{\mu}_t^n}{\hat{\sigma}_t^n},$$

where $\hat{\mu}_t^n$ and $\hat{\sigma}_t^n$ are non-parametric estimators of the drift and diffusion of dp_t. These can be obtained using a kernel-weighted average $K(x)$ of observations in the vicinity of t. The bandwidth h_n determines how fast observations are downweighted when they occur farther away from t:

$$\hat{\mu}_t^n = \frac{1}{h_n}\sum_{i=1}^{n} K\left(\frac{t_{i-1}-t}{h_n}\right) r_{t_i}, \qquad and \qquad \hat{\sigma}_t^n = \sqrt{\frac{1}{h_n}\sum_{i=1}^{n} K\left(\frac{t_{i-1}-t}{h_n}\right) r_{t_i}^2}$$

with $K_2 \equiv \int K(x)^2 dx$.

If the price is moving fast relative to the volatility T_t^n is large. Christensen, Oomen, and Renò (2018) show that in absence of a "drift burst" and under the assumption that dp_t follows the process (7), the test statistics T_t^n converges asymptotically to:

$$T_t^n \to \begin{cases} N(0,1) & \text{If no drift burst} \\ \infty & \text{If drift burst} \end{cases},$$

As $n \to \infty, h_n \to 0$, and $nh_n \to \infty$.

We employ a 30-minute bandwidth for the mean and a 60-minute bandwidth for the volatility. This means that, by construction, we are interested in flash crashes which develop on a time span of roughly 30 minutes. We also set $K(x) = exp(-|x|)1_{x\leq 0}$.

We compute the above test statistic every second during the course of a trading session. A significant negative value of T_t^n reveals a large and fast drop in price. We define the "beginning" of the crash t_0 the first time $T_{t_0}^n$ crosses -2.576 – corresponding to a p-value of 0.01 – from above. The "peak" of the crash, on the other hand, is defined as time t_1 such that $T_{t_1}^n$ reaches its minimum level. Accordingly, $\tau = t_1 - t_0$ is defined as the duration of the crash. However, an additional condition needs to be satisfied in order for an event to be defined as a "Flash Crash", namely that the stock experiences a cumulative price drop of at least 1% during the 30-minutes interval.

We apply the described methodology the universe of $2,700$ stocks from our original sample, using minute-by-minute price changes constructed from the Trades and Quotes database covering the period from 1997 to 2015. The procedure results in the identification of $10,572$ distinct flash-crash events, which are mostly evenly distributed across time and affect $1,849$ stocks (about 1 crash every three years for each stock, on average). These events represent significant price drops materializing in a relatively short time. The average drawdown during the 30-minute window is -2.06% (median -1.60%).

To test our first hypothesis, we construct a dummy variable indicating the presence of a flash-crash in a given stock-day and we run regressions on the panel of daily gamma imbalance estimates for the $1,849$ stocks that experienced a flash crash:

$$I_{Crash}(j,t) = \alpha + \beta_0 \Gamma^{IB}_{j,t-1} + FE_{j,t} + \varepsilon_{j,t},$$

where $I_{Crash}(j,t)$ is the dummy indicating a flash crash for stock j on day t and $\Gamma^{IB}_{j,t-1}$ is the level of gamma imbalance for that stock measured at the end of the previous day. The results are summarized in Table VIII and show that the estimate for β_0 is negative across all specifications. The relationship between gamma imbalance and flash crashes is significant from a statistical perspective, but not so important from an economic perspective. Indeed, our estimates imply that a negative shift of one standard deviation in the stock gamma imbalance increases the probability of flash crash for that stock by roughly 5% relative to the unconditional probability. Next, to directly assess the extent to which gamma imbalance is related to the severity of flash crashes. Conditional on a "flash crash" identified by the previous methodology, we regress the cumulative event return from $t = 0$ to $t = 30$ onto our stock-level gamma imbalance proxy Γ^{IB} measured as of the previous trading day, controlling for implied volatility, trading volume during the event and the stock's Amihud ratio. Table IX summarizes the results, and indicates a negative relationship between the price drop during flash crash events and gamma imbalance of broker/dealers. The effect is highly statistically and economically significant across all specifications. The point estimates imply that a one standard deviation decrease in Γ^{IB} is associated to a 20 to 200 basis point larger price drop. It is important to stress that correlation does not imply causation and we certainly do not interpret these results as evidence that delta-hedging of option dealers can cause flash crashes; rather, our results are consistent with the view that gamma imbalance can work as a friction that may exacerbate price movements due to fundamental news or liquidity shocks.

Insert Table VII

B. The May 6th 2010 Flash-Crash

The May 6, 2010 Flash Crash generated significant interest both among regulators and academics. The reasons are simple. In a matter of only 36 minutes the U.S. stock first erased more than a trillion dollar of market capitalization. From a theoretical perspective this is hard to be reconciled with a frictionless market given that, by the time the market closed, the Dow index had already recovered from the initial losses almost completely and that no significant economic news marked the day. Indeed, both the press and regulators immediately announced their intention to investigate the event and conjectured that the cause of the event was the existence of market manipulation.

As we revisit in greater details the unfolding of these events, one fact appears particularly striking to us as it rhymes with the narrative played by the role of gamma imbalance as discussed earlier. Because of worries about the debt crisis in Greece, at the opening of the stock market and well before the occurrence of the ”flash crash”, the Dow had already started falling. Indeed, by 2:32pm the Dow had already dropped about 2%. After 2:32pm, the equity market entered the “flash crash” climax and accelerated its fall by dropping an additional 600 points in just 5 minutes. By 2:47pm the index had accumulated a loss of nearly 1,000 points. Interestingly, this price fluctuation occurred in the absence of any significant economic news and by 3:00pm the Dow had recovered most of its losses.

The Commodity Futures Trading Commission (CFTC) conducted an investigation and eventually the U.S. Department of Justice pressed charges on "22 criminal counts, including fraud and market manipulation" against Navinder Singh Sarao, a British financial trader. Later, he was found guilty of using spoofing algorithms: just prior to the flash crash, he placed orders for about $200 million worth of bets" on the E-mini S&P 500 stock index futures contracts that the market would fall, which were eventually replaced or modified 19,000 times before they were canceled. The CFTC argued that Sarao actions were "significantly responsible for the order imbalances in the derivatives market which affected stock markets and exacerbated the flash crash."[10] The CFTC argument is directly related to the core question of our paper. Indeed, while price manipulation is difficult in normal markets, spoofing can become effective in the presence of large order imbalances in the derivative market.

According to our theory and the results from the previous section, gamma imbalance could have played a role during the flash crash. To shed light on this issue, we investigate the level of market-wide Gamma Imbalance during the days preceding the flash crash, defined as the daily cross-sectional average of stock-level gamma imbalance. The first Panel of Figure 8 shows that the market gamma imbalance drops and moves into negative territory in the days leading to the crash, and it is recorded at -1.7 standard deviation units during May 6. This corresponds to a negative market-wide dollar imbalance of roughly -431 million U.S. dollars. The second Panel of Figure 8 shows that this value is statistically significantly different from the average and sits in the left tail of the distribution. The drop in gamma imbalance occurred reasonably quickly during the week leading to the flash crash. Indeed, one week before the flash crash the total gamma imbalance was positive at about 383 millions.

Even though we cannot claim a causal relationship between the negative level of gamma imbalance and the flash crash, this evidence suggests that the delta-hedging activity of option dealers can contribute to market fragility and increasing the magnitude of price drops. Given

[10] See, Brush, Silla, Tom Schoenberg, and Suzi Ring (April 22, 2015), "*How a Mystery Trader with an Algorithm May Have Caused the Flash Crash*", Bloomberg News.

the fast price drop and the negative gamma exposure, dealers likely sold a significant amount of index shares to keep their positions hedged. This could have consumed additional liquidity and increased the downward pressure on the price, thus enhancing the drop.

Insert Figure 8

V. Leveraged ETF and ETN

A recent literature suggests that a significant increase in adoption of leveraged ETFs has contributed to an increase in market volatility. Since leveraged ETFs provide a daily constant multiple of the underlying index, following any market move the ETF needs to daily rebalance its positions to maintain a constant leverage ratio. For example, a $4\times$ fund is designed to offer four times the daily index return, while a $-4\times$ fund is designed to generate four times the opposite return of the index. These funds achieve their target exposure to the index with a combination of swaps and futures. While leveraged ETFs are synthetic instruments, their swap counterparties have to rebalance to maintain the required exposure, regardless of market conditions. If L is the leverage multiple, the exposure E_t^* needs to be $L \times NAV_t$. Thus, if the return on the index at time $t+1$ is r_{t+1}, the E_{t+1}^* is equal to $L[NAV_t \times (1 + r_{t+1} \times L)]$. This implies that the required rebalancing at time $t+1$ is

$$E_{t+1}^* - E_t^* = L^2(r_{t+1} \times NAV_t)$$

When the market increases (e.g. $r_{t+1} > 0$), both levered long and short funds need to increase their notional principal, thus adding to any existing buying pressure that contributed to the initial price increase. When the market decreases (e.g. $r_{t+1} < 0$), both long and short funds are net sellers in the market. This implies that by the end of the trading day, the demand and supply of leveraged ETFs create additional demand or selling pressure in the same direction as the market move. This argument predicts that a greater adoption of leveraged ETFs and ETNs should correlate with greater price momentum in the hours before market close (Cheng and Madhavan (2009)).

Ben-David, Franzoni, and Moussawi (2018) find evidence that stocks owned by ETFs exhibit significantly higher overall daily volatility. They estimate that an increase of one standard deviation in ETF ownership is associated with an increase of 16% in daily stock volatility. They argue, similarly to us, about the existence of feedback effects due to the hedging activity of arbitrageurs active in the ETF market. Indeed, they find that the effects are stronger for stocks with lower bid-ask spread and lending fees. However, they do not study intraday patterns. Shum, Hejazi, Haryanto, and Rodier (2015) document the existence of a link between the rebalancing activity of leveraged ETFs and market volatility before market closure. Although related to our findings, these papers do not provide predictions about the coexistence of both intraday momentum and reversal. While the aggregate value of leveraged ETFs have increased almost monotonically in the last ten years, the frequency of positive price momentum has not monotonically increased over time. Instead, we observe both intraday price momentum and reversals. We test whether unusual intraday high (low) autocorrelation or/and volatility correlates with unusually high (low) aggregate notional of leveraged ETF and comfortably reject this hypothesis.

Finally, using cross-sectional data on individual stocks we document significant cross-sectional dispersion in price momentum and reversal which cannot be explained by the rebalancing activity of leveraged ETFs. At the same time, this cross-sectional dispersion correlates with cross-sectional differences in gamma imbalance.

VI. Conclusion

This paper provides evidence supporting the view that trading in derivatives may affect the price process of the underlying assets, contributing to intraday stock volatility and auto-correlation by increasing (dampening) the initial effect of news on market fundamentals.

Indeed, we unveil a strong negative relationship between the gamma imbalance of option dealers and measures of intraday volatility. This phenomenon is relevant both for market participants and regulatory concerned about market fragility. This effect might become even more important in the future given the increasing incentived for institutions to use derivative products with non-neutral gamma to reduce their required regulatory risk capital.

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VII. Tables

Table I. Option Data - Summary Statistics

This table presents summary statistics of the main variables employed in the analysis. We consider put and call options written on a universe of 2700 US equity stocks over the period from December 2010 to May 2020. The gamma imbalance proxies Γ^{IB} are defined in Section II.B and expressed in percentage units. The open interest is expressed in contracts units, while the trading volume of the underlying assets is in million dollars. Absolute values of returns and daily spreads are in basis points.

	Observations	Mean	Std	10%	25%	50%	75%	90%
Dealers Gamma Imbalance	3,666,122	13.513	124.513	-14.631	-0.844	0.054	3.799	37.455
Options Open Interest	3,666,122	107,364	294,046	186	1,277	9,899	63,436	259,231
Options Implied Volatility	3,666,122	0.552	0.315	0.260	0.332	0.459	0.672	0.974
Underlying Volume	3,666,122	2.127	3.686	0.146	0.334	0.846	2.173	5.136
Underlying Absolute Return	3,666,122	184.599	205.611	19.008	51.089	118.824	239.188	424.312
Underlying Daily Spread	3,666,122	336.449	253.295	116.670	168.292	260.869	416.771	646.806
Underlying Amihud Ratio	3,666,122	4.915	6.403	0.486	1.208	2.921	6.346	10.751

Table II. Gamma Imbalance and Volatility

The dependent variable of this panel regression is the absolute value of day-t return of asset j, expressed in basis points. The main explanatory variable is Γ^{IB}, i.e. the dollar *gamma imbalance* of broker/dealers on put and call options written on j as of the close of day $t-1$, expressed as a fraction of the average daily volume of the underlying. We control for the option-implied volatility as of $t-1$ and we saturate the model with asset and month fixed effects. All regressors are standardized and winsorized at the 1% level. T-stats are reported in parentheses, based on robust standard errors double-clustered at the asset and month level. Asterisks denote significance levels (***= 1%, **= 5%, *= 10%).

	(1)	(2)	(3)	(4)
Dependent Variable	|Return|	|Return|	|Return|	|Return|
Gamma Imbalance (lag)	-5.069 ***	-13.282 ***	-24.833 ***	-12.075 ***
	(-4.035)	(-10.059)	(-16.587)	(-11.460)
Implied Volatility (lag)	103.340 ***	71.555 ***	73.179 ***	46.913 ***
	(42.021)	(7.295)	(77.035)	(20.786)
Stock Fixed Effects		Yes		Yes
Time Fixed Effects			Yes	Yes
R-squared	0.521	0.054	0.114	0.021
Observations	3,666,122	3,666,122	3,666,122	3,666,122
Ses Clustered By	Stock-Time	Stock-Time	Stock-Time	Stock-Time

Table III. Index Options

These specifications are the same as the ones presented in Table II, but we restrict to to options on market indices. The universe includes S&P 500, Dow Jones, Nasdaq 100 and Russell 2000. The gamma imbalance proxy for this regression is constructed from Option Metrics and it is based on the assumption that broker/dealers are mainly short put options and long call options. It is defined as $\Gamma_1^{IB}(t) = \left(\Gamma^{\$}_{Call}(t) - \Gamma^{\$}_{Put}(t)\right)/\mathrm{ADV}(t)\times 100$. We control for the option-implied volatility as of $t-1$ and we saturate the model with asset and month fixed effects. T-stats are reported in parentheses, based on robust standard errors double-clustered at the asset and month level. Asterisks denote significance levels (***= 1%, **= 5%, *= 10%).

	(1)	(2)	(3)	(4)
Dependent Variable	|Return|	|Return|	|Return|	|Return|
Gamma Imbalance (lag)	-14.79***	-14.78**	-6.62**	-5.49**
	(-4.42)	(-3.75)	(-3.64)	(-3.33)
Implied Volatility (lag)	410.28***	402.19***	330.11***	278.81***
	(9.73)	(7.57)	(9.36)	(6.88)
Constant	-138.77***			
	(-5.15)			
Observations	21,434	21,434	21,434	21,434
R-squared	0.252	0.253	0.341	0.358
Stock Fixed Effects		Yes		Yes
Time Fixed Effects			Yes	Yes
Ses Clustered By	Stock-Time	Stock-Time	Stock-Time	Stock-Time

Table IV. Control for Past Volatility

In this specification we add controls for past volatility, to account for the fact that volatility is a highly persistence process. We include lagged values of the absolute value of returns by 1, 2 and 3 business days. We also control for the option-implied volatility as of $t-1$ and we saturate the model with asset and month fixed effects. T-stats are reported in parentheses, based on robust standard errors double-clustered at the asset and month level. Asterisks denote significance levels (***= 1%, **= 5%, *= 10%).

	(1)	(2)	(3)	(4)
Dependent Variable	|Return|	|Return|	|Return|	|Return|
Gamma Imbalance (lag)	-2.725 ***	-8.571 ***	-17.774 ***	-9.144 ***
	(-3.161)	(-7.638)	(-15.419)	(-10.625)
Implied Volatility (lag)	65.810 ***	49.668 ***	54.160 ***	37.502 ***
	(37.453)	(12.119)	(68.430)	(25.910)
|Return| (1 day lag)	0.147 ***	0.130 ***	0.112 ***	0.094 ***
	(16.593)	(10.125)	(32.697)	(26.555)
|Return| (2 day lag)	0.119 ***	0.102 ***	0.085 ***	0.068 ***
	(10.987)	(7.005)	(28.237)	(17.522)
|Return| (3 day lag)	0.097 ***	0.080 ***	0.065 ***	0.047 ***
	(11.378)	(6.415)	(28.280)	(14.442)
Stock Fixed Effects		Yes		Yes
Time Fixed Effects			Yes	Yes
R-squared	0.551	0.096	0.141	0.039
Observations	3,655,669	3,655,669	3,655,669	3,655,669
Ses Clustered By	Stock-Time	Stock-Time	Stock-Time	Stock-Time

Table V. Interaction with Illiquidity

In these specifications we further explore the heterogeneity of our baseline results conditional on the level of liquidity of the underlying assets, proxied by the Amihud illiquidity ratio. We interact the *dollar* gamma imbalance proxy $\Gamma_{\$}^{IB}$ with a dummy indicating the most illiquid underlying assets, i.e. those below the median Amihud ratio. For each underlying asset, the illiquidity ratio at time t is computed on a two-year rolling window ending one month before day t and then averaged across the sample period. We control for the option-implied volatility as of $t-1$ and we saturate the model with asset and month fixed effects. T-stats are reported in parentheses, based on robust standard errors double-clustered at the asset and month level. Asterisks denote significance levels (***= 1%, **= 5%, *= 10%).

	(1)	(2)	(3)
Dependent Variable	|Return|	|Return|	|Return|
Low Liquidity	18.273 ***		18.698 ***
	(10.202)		(10.398)
Dollar Gamma Imbalance (lag)		-3.218 ***	-1.299
		(-3.968)	(-1.344)
Dollar Gamma Imbalance (lag) × Low Liquidity			-8.882 ***
			(-7.614)
Implied Volatility (lag)	99.277 ***	103.350 ***	99.235 ***
	(36.137)	(42.013)	(36.103)
R-squared	0.523	0.521	0.523
Observations	3,666,122	3,666,122	3,666,122
Ses Clustered By	Stock-Time	Stock-Time	Stock-Time

Table VI. Intra-day Auto-Correlation

In these specifications the dependent variable is the auto-correlation coefficient of intra-day returns of the underlying assets at various frequencies (5, 10, 20, 30 and 60 minutes), computed from the TAQ dataset. In every specification we control for implied volatility as of day $t-1$ and the dollar trading volume during day t. T-stats are reported in parentheses, based on robust standard errors double-clustered at the asset and month level. Asterisks denote significance levels (***= 1%, **= 5%, *= 10%).

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	5 Min AC	10 Min AC	20 Min AC	30 Min AC	60 Min AC
Gamma Imbalance (lag)	-1.814 ***	-1.469 ***	-1.619 ***	-1.552 ***	-1.984 **
	(-4.830)	(-2.781)	(-2.794)	(-2.641)	(-2.350)
Traded Volume	0.000 ***	0.000 ***	0.000 ***	0.000 ***	0.000 ***
	(25.706)	(20.073)	(17.030)	(20.702)	(3.946)
Implied Volatility (lag)	0.011	-0.034	0.059	0.015	-0.495 **
	(0.195)	(-0.476)	(0.585)	(0.155)	(-2.385)
Stock Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
R-squared	0.003	0.002	0.002	0.002	0.000
Observations	1,541,400	1,541,400	1,541,398	1,541,400	1,541,313
Ses Clustered By	Stock-Time	Stock-Time	Stock-Time	Stock-Time	Stock-Time

Table VII. Gamma Imbalance and Daily Spread

The dependent variable of this panel regression is the *daily spread*, an alternative measure of intra-day volatility defined as $S = (H - L)/(H + L) \times 2 \times 1000$, where H is the highest ask price for asset j in day t and L is the lowest bid price. We control for the option-implied volatility as of $t - 1$ and we saturate the model with asset and month fixed effects. T-stats are reported in parentheses, based on robust standard errors double-clustered at the asset and month level. Asterisks denote significance levels (***= 1%, **= 5%, *= 10%).

	(1)	(2)	(3)	(4)
Dependent Variable	Spread	Spread	Spread	Spread
Gamma Imbalance (lag)	-10.741 ***	-18.207 ***	-40.030 ***	-15.980 ***
	(-5.790)	(-9.563)	(-17.719)	(-10.246)
Implied Volatility (lag)	190.450 ***	119.930 ***	147.820 ***	85.678 ***
	(56.659)	(8.234)	(83.703)	(19.814)
Stock Fixed Effects		Yes		Yes
Time Fixed Effects			Yes	Yes
R-squared	0.762	0.131	0.322	0.065
Observations	3,666,122	3,666,122	3,666,122	3,666,122
Ses Clustered By	Stock-Time	Stock-Time	Stock-Time	Stock-Time

Table VIII. Gamma Imbalance and Flash Crashes

The dependent variable of this panel regression is a dummy variable Flash Crash(j, t) which equals to one if stock j experiences a flash crash during day t. Flash crashes are identified applying the algorithm proposed by Christensen, Oomen, and Reno' (2017) to minute-by-minute prices constructed from the TAQ database. The table reports results from a regression of Flash Crash(j, t) onto the Gamma Imbalance of dealers on put and call options written on stock j as of the close of day $t-1$, expressed as a fraction of the average daily volume of the underlying. In specifications (2), (3) and (4) we saturate the model with day and stock fixed effects. T-stats are reported in parentheses, based on robust standard errors double-clustered at the asset and date level. Asterisks denote significance levels (***= 1%, **= 5%, *= 10%).

	(1)	(2)	(3)	(4)
Dependent Variable	Flash Crash	Flash Crash	Flash Crash	Flash Crash
Gamma Imbalance (lag)	-0.401	-0.723 **	-1.150 ***	-0.561 *
	(-1.380)	(-2.170)	(-2.966)	(-1.780)
Implied Volatility (lag)	0.127 ***	0.003	0.090 ***	0.033 **
	(3.478)	(0.080)	(3.345)	(2.553)
Stock Fixed Effects		Yes		Yes
Time Fixed Effects			Yes	Yes
R-squared	0.002	0.000	0.000	0.000
Observations	3,666,122	3,666,122	3,666,122	3,666,122
Ses Clustered By	Stock-Time	Stock-Time	Stock-Time	Stock-Time

Table IX. Gamma Imbalance and Magnitude of Flash Crashes

The dependent variable of this panel regression $\text{EventReturn}_i(t)$ is the cumulative return stock i experiencing a flash crash event, from event time $t = 0$ to $t = 30$ minutes ($\text{EventReturn}_i(t) < 0$ for all observations). Flash crashes are identified applying the algorithm proposed by Christensen, Oomen, and Reno' (2017) to minute-by-minute prices constructed from the TAQ database. The table reports results from a regression of Flash $\text{Crash}(j, t)$ onto the Gamma Imbalance of dealers on put and call options written on stock j as of the close of day $t - 1$, expressed as a fraction of the average daily volume of the underlying. In specifications (2), (3) and (4) we saturate the model with day and stock fixed effects. T-stats are reported in parentheses, based on robust standard errors double-clustered at the asset and date level. Asterisks denote significance levels (***= 1%, **= 5%, *= 10%).

	(1)	(2)	(3)	(4)
Dependent Variable	Event Return	Event Return	Event Return	Event Return
Negative Gamma Imbalance	-210.950 ***	-27.182 ***	-22.507 ***	-19.378 ***
	(-22.291)	(-5.526)	(-4.689)	(-4.161)
Implied Volatility (lag)		-85.769 ***	-80.709 ***	-75.945 ***
		(-17.527)	(-18.947)	(-17.487)
Traded Volume			-0.000 ***	-0.000 ***
			(-9.464)	(-9.052)
Amihud Ratio				-3.072 ***
				(-8.320)
Stock Fixed Effects				
Time Fixed Effects				
R-squared	0.338	0.747	0.756	0.756
Observations	11,405	11,405	11,405	11,405
Ses Clustered By	Stock-Time	Stock-Time	Stock-Time	Stock-Time

VIII. Figures

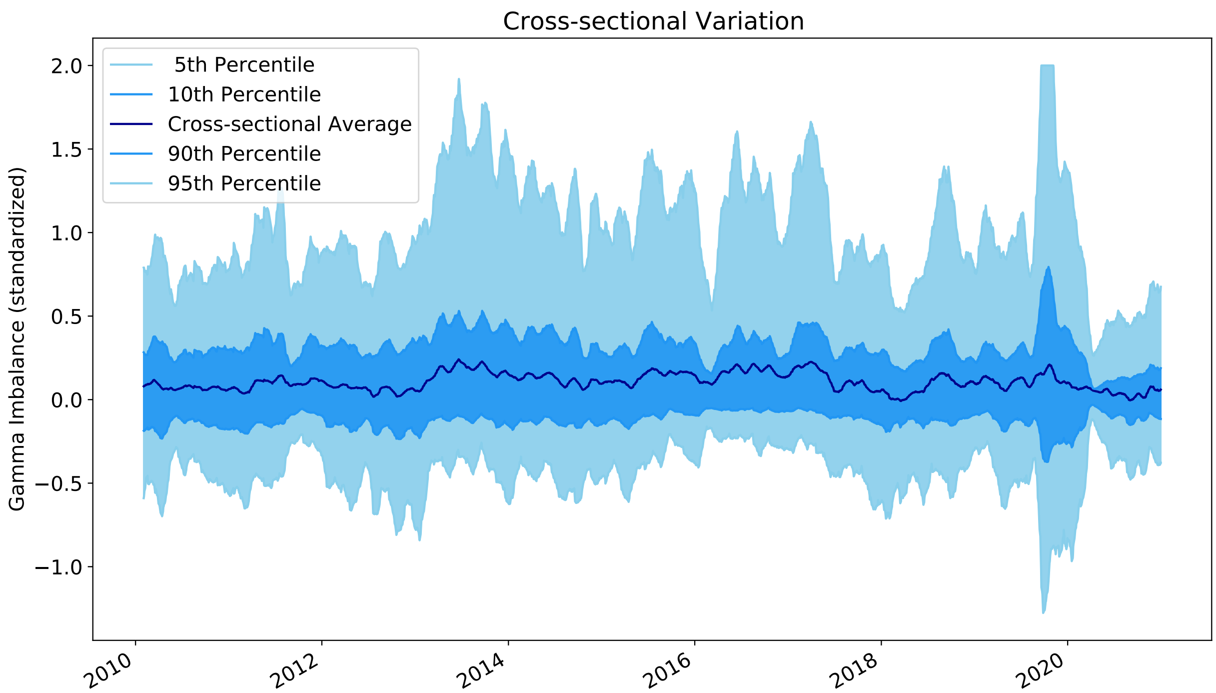

Figure 4. Gamma Imbalance – Panel Variation
The figure displays cross-sectional and time-series variation of gamma imbalance $\Gamma^{IB}(t)$ for the assets in our sample, defined at the daily-stock level as in equation , that is, the dollar value of gamma-weighted positions of broker/dealers as a fraction of the stocks average daily volume. The blue line is the cross-sectional average for day t, while the light-blue area represents the interval between the 10th and 90th percentiles in the day-level distributions of the variable, while the darker blue area represents the interval between the 25th and 75th percentiles.

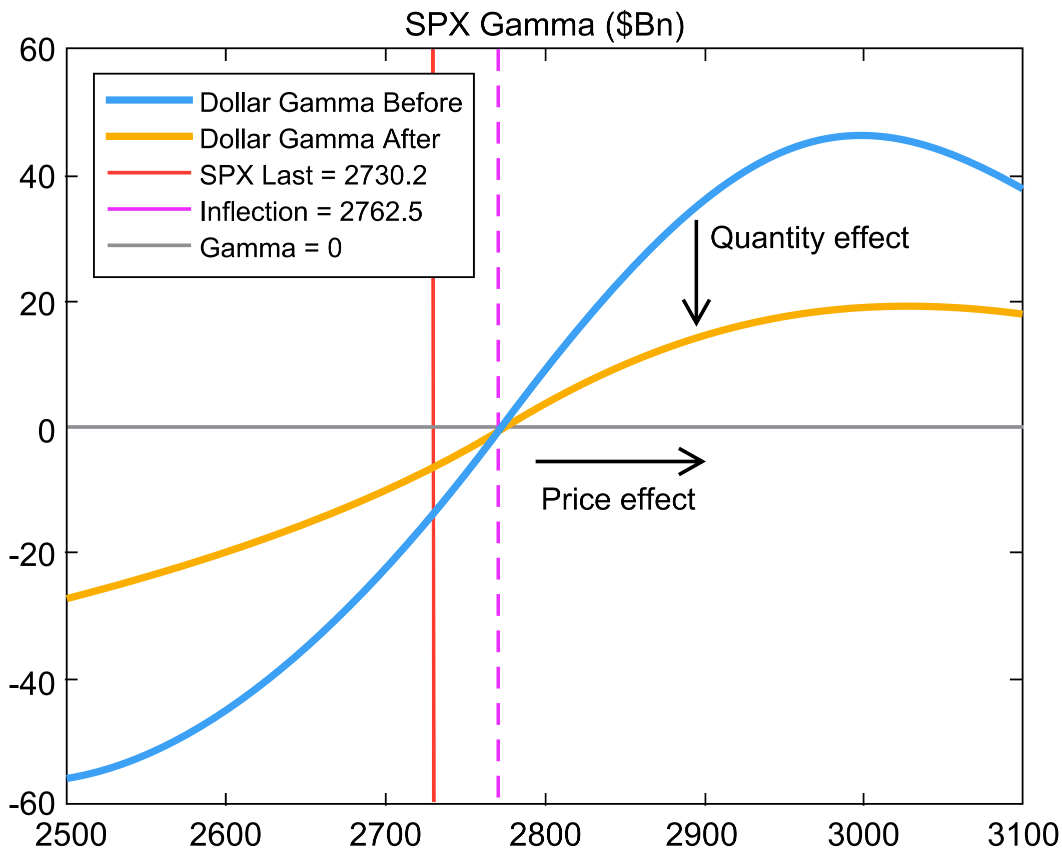

Figure 5. Gamma Inflection Point

This Figure shows how the aggregate Gamma changes as a function of the level of the underlying asset. The figure refers to November 15th ("Before") and 16th 2018 ("After") for options on the SP500. The "Inflection" is defined as the level of the SP500 at which aggregate Gamma is zero.

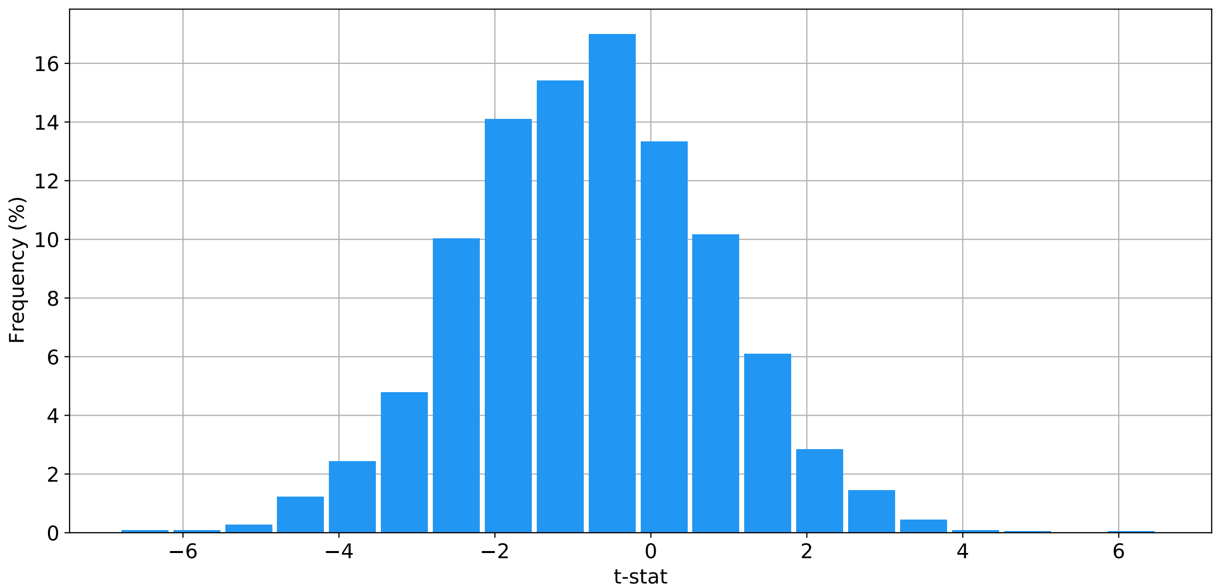

Figure 6. Distribution of t-statistics

The top panel in the figure shows the distribution of the t-statistics on the beta coefficient from the following time-series regressions run on each of the 2704 assets in our sample:

$$\mid R_t \mid = \alpha + \beta\,\Gamma^{IB}_{t-1} + \varepsilon_t,$$

where $\mid R_t \mid$ is the absolute value of the asset return on day t and Γ^{IB}_{t-1} is our proxy for the degree of gamma imbalance of dealers as-of the previous day closure, defined in Section B. T-statistics are computed using the heteroskedasticity and autocorrelation consistent (HAC) standard errors from Newey and West (1986). The bottom panel is a scatter plot that summarizes the relation between the implied t-statistics and the log open interest of the options written on the corresponding security.

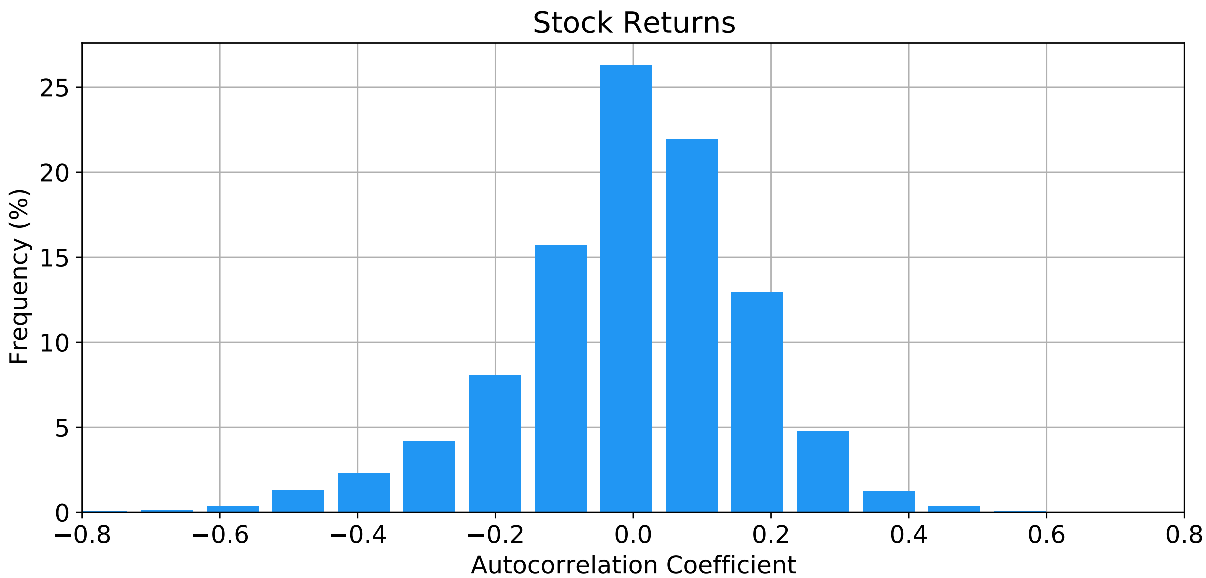

Figure 7. Distribution of Autocorrelation Coefficients

The figure shows the distribution of intraday autocorrelation coefficients for equity returns sampled at the 5-minutes frequency, computed at the stock-hour level.

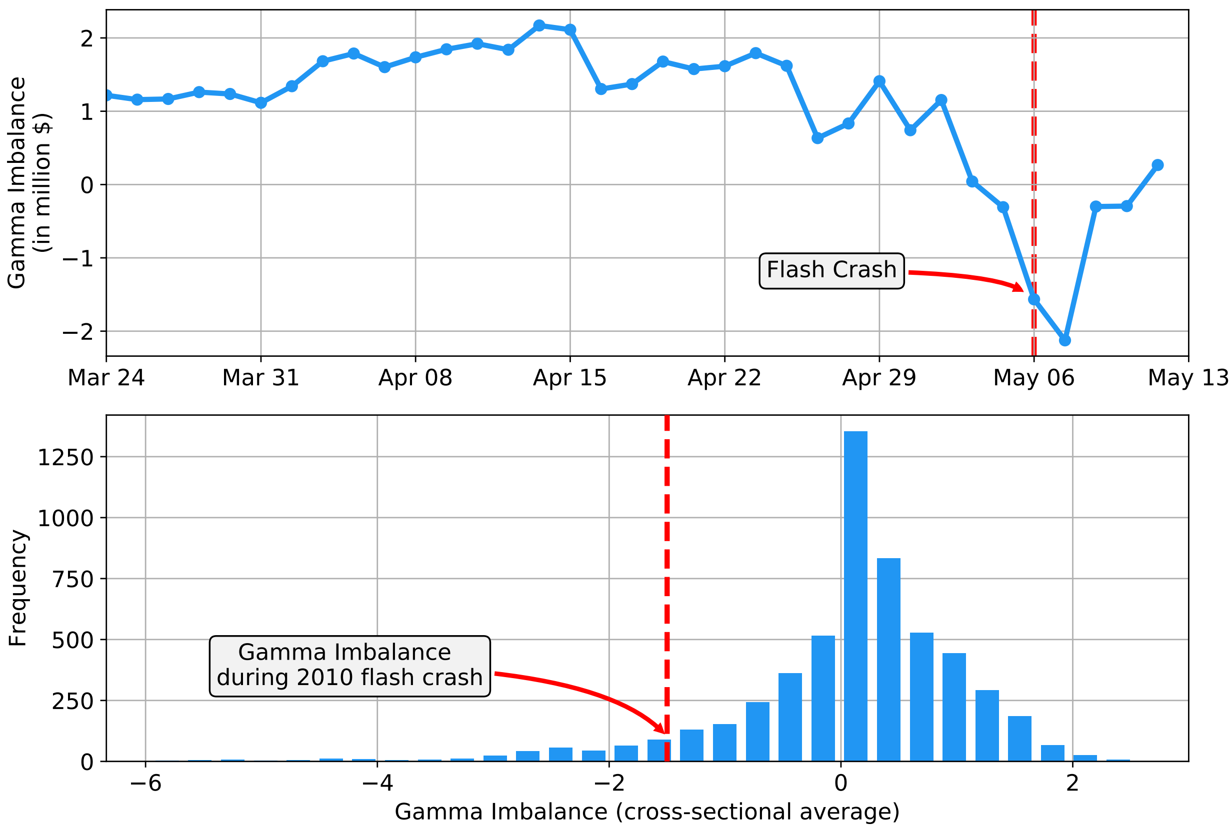

Figure 8. Gamma Imbalance during 2010 Flash Crash
The top panel of the figure shows the time-series evolution of market-wide gamma imbalance, that is the daily cross-section average of stock-level gamma imbalances in standard deviation units, around the flash crash of May 6, 2010. On that date, the total market-wide dollar imbalance was negative at roughly −431 million US Dollars. The bottom panel presents the distribution of market-wide gamma imbalance, with the vertical dashed line representing the value on May 6, 2010.